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EVALUATION

Empirical essays on labor-force participation, matching, and trade

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Abstract

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This thesis consist of four self-contained essays.

Essay I estimates the macroeconomic effect of labor market programs on labor-force participation. The results indicate that labor market programs have relatively large and positive effects on labor-force participation. If the number of participants in programs is permanently increased, the labor force increases by about 70 persons in the long run. The positive effect of labor market programs is larger in down-turns.

Essay II examine if the flow rate from open unemployment to labor market programs affect the labor-force participation rate. The results show that increased probability of moving from open unemployment to labor market programs have positive effects on the labor-force participation rate. The positive effects are found for different age groups. The estimated effect is countercyclical.

Essay III deals with the long-run behavior of Swedish exports and export prices. I find that i) the cointegration analysis supports the hypothesis of a "long-run" demand function for Swedish exports; ii) the foreign trend and the domestic labor trend are equally important for exports in the long-run; iii) the domestic labor trend is the most important factor behind the changes in the relative prices; and iv) the productivity trend is important for real wages.

Essay IV (with Anders Forslund) estimates empirical matching functions for Sweden, with focus on time aggregation problem, and on stock-flow matching. The parameter estimates in all estimated models forcefully reject random matching but are consistent with stock-flow matching. There is evidence of time aggregation problem in our results, and it provides a warning against over-confidence in estimates of the scale elasticity of the matching function derived from annual or quarterly data, if no account is taken to the within period inflow of job-seekers and vacancies.

Acknowledgements

First of all I want to thank my advisor Anders Forslund for stimulating discussion about almost everything; economics, music[1], bicycling, swimming[2], and other things. Anders has been a great advisor and a good friend during these years. The door to his room has always been open, and he has had time to discuss and answer my questions. He has been supportive, and has let me work in my own way, which is something that I really appreciate.

My career as a researcher started when I was admitted to the graduate program in economics in Stockholm, 1991. I wrote my undergraduate thesis while working at the National Institute of Economic Research, NIER, (Konjunkturinstitutet). My advisor then, Torsten Persson, Institute for International Economic Studies, (IIES), in Stockholm, encouraged me to start at the doctoral program. IIES was my first experience of the academic world and it was an extremely intellectual and stimulating environment. There, I got in contact with several persons that become important for me. In particular, my thesis advisors, Nils Gottfries and Anders Warne, whom I really want to thank for their enthusiasm, and interest in my work. During my time at IIES I especially want to mention and thank Petter Lundvik[3], Gunnar Jonsson, Magnus Dahlkvist, Johan Stennek, and a great many other people.

I completed the course program in Stockholm, and I defended my licentiate thesis in 1994. I went back to my old place of work, and stayed at NIER for five years before it was time to search for a new job. During the search process, I told several persons that I was looking for a new job, and one of them was Lars Calmfors, who told Susanne Ackum (at that time director of IFAU, Institute for Labour Market Policy Evaluation, in Uppsala) that I was looking for a new job. Several months later, she called me and invited me to apply for a job at IFAU. One of the requirements was that I should finish

[1]He is the only one at IFAU who likes to listen to Frank Zappa. :-)

[2]Like experiences of the difficulties when trying to learn new swimming techniques as a grown up.

[3]Petter was also my boss during the last months of my stay at NIER.

my dissertation. I started to work at IFAU and moved to Uppsala in 1999. Comparing all different job places that I have been to, IFAU has been the best, so thanks to Lars Calmfors who made my time at IFAU possible.

The institute had been founded recently, the staff was young and enthusiastic, and the director, Susanne Ackum, were very enthusiastic and encouraging. The environment at IFAU was stimulating, with frequent contacts with the Department of Economics at Uppsala University. For me, it was a new experience to get in touch with people using micro data and evaluating the policy effects on individuals. Thank you very much Susanne for giving me the opportunity to finish my thesis, and for your enthusiasm and support, which I really needed on many occasions. Thanks also to my co-advisor Kenneth Carling and to Kåre Johansen, Magnus Wikström, Matz Dahlberg, Bertil Holmlund, Johan Lindén, and Erik Mellander for valuable comments during different stages of the process. Special thanks also to Peter Fredriksson (the new director at IFAU) for suggestions and help. Peter has also generously allowed me to work part-time at the IFAU while I was starting up my new business, help that I really appreciate.

I want to thank all my colleagues at IFAU and all other people that I have been in contact with during the writing of this thesis. In particular, I want to mention Katarina Richardsson, Eva Mörk, Linus Lindqvist, Björn Öckert, P-A Edin, Helge Bennmarker, Per Johansson, and Oskar Nordström Skans. Also, thanks to the competent and patient administrative staff and IT department at IFAU.

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Uppsala, August 2006
Kerstin Johansson

[4]MIAU

Contents

Introduction*

This dissertation consists of four empirical essays in different fields. Essays I and II deal with the macroeconomic effects of labor market programs on labor-force participation. These essays use panel data to estimate the effect of labor market programs. Essay III is the oldest and it contains an empirical model of trade, applied to the determination of Swedish exports and export prices, between 1970-1992. Essay IV, written together with Anders Forslund, examines empirical aggregate matching function for the Swedish labor market.

All of the essays have a macro-economic perspective, both with respect to the theory and empirics. Three of the four essays are related to labor economics, and have been written in recent years. The essay on Swedish exports is my licentiate thesis which I defended in Stockholm in 1994. The links between the three labor market essays and the export essay are weak; they were written at different times, in different places, and under different circumstances. The common factor is that simple macro models are used and that these models seem to capture important features of the data.[1] Of course, the number of questions that could be asked is limited, compared to when micro data is used, for example. On the other hand, the advantage is that we readily achieve an overview of some important economic relationships.

Do labor market programs affect labor-force participation?

The background to Essays I and II is that Sweden's labor-force participation rate, measured as the number of persons in the labor force relative to the number of persons in the working age population, declined sharply in the 1990s, from an average of 84 % during the late 1980s to 79 % in the 1990s. The unemployment rate, measured in terms of the working-age population,

*Comments from Anders Forslund and Erik Mellander are gratefully acknowledged.

[1]It is surprising that the models fit to the data, because the underlying assumptions regarding aggregation of individuals' behavior are strong.

increased during the same period from an average of 2 % to almost 6 %, and the number of participants in labor market programs in relation to the working age population rose from around 1 % in the late 1980s to more than 3 % in the 1990s.

Very few studies concern the effects of labor market programs on labor-force participation. The question is important in Sweden because the labor force is expected to decline, due to the age distribution of the population. Labor market programs could play a role in attracting new entrants to the labor force and preventing participants from leaving the labor force. Today, a lot of attention is spent on how to attract groups outside the labor force into it.

It is important for the overall performance of the labor market that movements into and out of labor force occur without frictions. In Sweden, labor-force participation is pro-cyclical, so people tend to leave labor force when it is difficult to find a job and to enter when it is easy to find a job. Programs could be used to counteract this business cycle variation in labor-force participation, and perhaps prevent people from leaving the labor force permanently.

Why two essays on labor market programs and labor-force participation?

Essays I and II are similar in some respect. Virtually the same question is asked and almost the same kind of data are used in the two essays. But, nonetheless, the difference between the two essays is considerable, because the policy questions are different. Essay I asks whether the number of participants in labor market programs affects the number of labor force participants, (holding the population constant), while Essay II asks whether the flow rate from open unemployment to labor market programs affects the labor-force participation rate. The same theoretical model is, however, used as a background in both essays.[2]

The main reason for writing two essays about almost the same subject is that, on the one hand, the stock data used in Essay I make the results comparable with findings obtained in other studies while, on the other hand the monthly data in Essay II have some advantages compared to the yearly data in Essay I. Specifically, with the monthly data it is possible to pose a different, and maybe clearer policy question. The flow from open unemployment to labor market programs may be controlled more directly by the

[2]The same theoretical model is presented in Essays I and II, which should not confuse the reader. This is so because the essays should be regarded as self-contained.

policy-makers than the stocks. The stocks can only be controlled indirectly, by changing the inflow or the average program duration. A typically question like "What happens to labor-force participation if we move 100 openly unemployed persons into labor market programs?" can only be answered using results from the analysis in Essay II, where flows are used.

Even if I have argued that the policy experiment in Essay II is clearer, Essay I is still interesting. One reason for using stocks is that the results can be compared with results that are obtained in other studies. Moreover, data on stocks are normally more reliable, because they are measured with more accuracy. If there are measurement errors in the dates, the flows will be more greatly affected than the stocks because the flows are smaller and the variation in the flows is larger than the variation in the stocks.

From a policy perspective, the question about what happens if we move 100 persons from open unemployment into labor market programs is relevant, and the flows describe the tools for the policy implementation because they can be controlled directly by the local authorities. But, on the other hand, during the sample period, there has been political targets for the number of program participants. Models based on stocks may be used to ask questions about the effect of changes in targeting. Stocks are also interesting because their connection to the economic activity is clearer. For example, models that describe the behavior of wages and prices are often based on stocks. We have more knowledge about the cyclical behavior of stocks, because data on stocks are more common than data on flows. Sometimes, it might also be an advantage that the question that to be answered is less specific. We could then interpret the estimation results as indications of the effects of several possible experiments.

Empirical results

The results in Essays I and II are that both increased stock of program participants and increased flow from open unemployment into labor market programs have positive effects on labor-force participation. The estimated effects are larger in downturns. The participation rate is pro-cyclical, and counter-cyclical labor market programs could be used to attract people to participate in the labor force, alternatively to prevent people from leaving the labor force.

Essay I *"Labor market programs, the discouraged-worker effect, and labor-force participation"* estimates the macroeconomic effect of labor market programs on labor-force participation. An equation that determines the labor-force participation rate is estimated on panel data for Sweden's municipalities, during the period 1986-1998. The results indicate that labor market programs have relatively large and positive effects on labor-force participation. If the number of participants in labor market programs temporarily increases by 100, the labor force increases immediately by around 63 persons. The effect is temporary so the number of labor force participants returns gradually to the old level. If the number of program participants is permanently increased, the labor force increases by about 70 persons in the long run. Programs reduce the business-cycle variation in labor-force participation because the effect is positive and programs have been counter-cyclical, in the period studied. The results indicate that programs could prevent labor force outflow; participants who would have left the labor force if there were no programs may now be participating as a result of the programs. Higher wages and more vacancies increase the participation rate, both in the short and the long run. Open unemployment, the job destruction rate, and the proportion of persons in the 18-24 and 55-65 age groups have negative long run effects on the participation rate.

Essay II *"Do labor market flows affects labor-force participation?"* examines the question of whether the flow rate from open unemployment to labor market programs affects the labor-force participation rate. A new dataset, with monthly data for the Swedish municipalities between 1991:08 and 2002:10 has been established. The results show that an increased likelihood of moving from open unemployment to labor market programs has positive effects on the labor-force participation rate. These positive effects apply to different age groups. The estimated effect of the flow rate from open unemployment into labor market program is countercyclical, and the expected effect is larger in downturns. The participation rate is pro-cyclical, and counter-cyclical labor market programs could be used to prevent discouraged workers from leaving labor force. The effects of flow rates from programs to open unemployment, and from the job destruction rate are negative, as expected. Income and labor market tightness have positive effects, except for older participants. In general, the long run levels are achieved after about nine years, and most of the adjustment takes place during the first four years.

The long run determinants of Swedish exports

The motivation for Essay III *"Common Trends in Exports"* was to use, at that time, modern multivariate time series methods to shed some light on an old empirical question, namely how to estimate the price elasticity of foreign trade. A traditional approach was used, but the empirical model was new. But in the early 1990:s, time series methods were developing rapidly with an enormous number of empirical papers using cointegration methods. The common trend model used in Essay III is derived from the moving average representation of a cointegrated vector autoregressive system (VAR). Factors underlying the long run effect are separated from factors determining the short run effects. A simple general equilibrium model is used to theoretically determine the expected effects of these shocks. The theoretical model is also used to generate the restrictions needed for the long run behavior of the common trends model.

A common trend model, which includes exports, foreign expenditure, relative prices and real wages, is estimated on yearly data for 1970-1992. Three long run factors are identified, two domestic trends, representing labor supply and productivity, and one foreign trend. I find that i) the cointegration analysis supports the hypothesis of a "long-run" demand function for Swedish exports; ii) the foreign trend and the domestic labor trend are equally important for exports in the long-run; iii) the domestic labor trend is the most important factor behind the changes in relative prices; and iv) the productivity trend is important for real wages.

Random or stock flow matching in Sweden

Essay IV, *"Random and stock-flow models of labour market matching - Swedish evidence"*, is written together with Anders Forslund, and we estimate an empirical aggregate matching function for the Swedish labor market. A recent survey by Petrongolo and Pissarides (2001) indicates that the matching function has been unstable, and decreased matching efficiency is one explanation. Other reasons for the instability observed have been suggested. For example, Gregg and Petrongolo (2004), argue that it reflects mis-specification problems, when data on stocks and flows in discrete time are used. Another candidate for mis-specification is that the matching process is characterized by stock-flow matching, instead of the random matching that is normally assumed.

In models with random matching, it is assumed that job seekers and vacancies are matched randomly. No distinction is made between job seekers or vacancies that have been on the market for different lengths of time. They have the same matching probabilities, regardless of how long the jobs have been vacant, or how long the job seekers have been unemployed. In stock-flow models of matching, there is a distinction between new and old vacancies, and new and old job seekers. The new vacancies and job seekers are measured by the inflow during a period, and the old vacancies and job seekers are measured by the stock at the beginning of the period. It is assumed that new job seekers match with old and new vacancies, and that the stock of old job seekers only matches the inflow of new vacancies.

In Essay IV, we estimate aggregate matching functions, focusing on time aggregation problems and on stock-flow matching. We have a rich dataset that enables us to compute data at any frequency that we want. We choose weekly data, to address the question of the importance of the time aggregation problem, and we estimate models that allow for stock-flow matching. The parameter estimates forcefully reject random matching but are consistent with stock-flow matching. A non-trivial share of new job-seekers matches within the first week. The stock of old vacancies and job seekers does not contribute significantly to matching, whereas the inflow of vacancies matches with the lagged stock of job seekers.

Our estimation results indicate that the time aggregation problem, which could result in downward bias of the parameter estimates, is present. This evidence of the problem with time aggregation provides a warning against over-confidence in estimates of the scale elasticity of the matching function derived from annual or quarterly data, if no account is taken of the within-period inflow of job-seekers and vacancies.

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Essay I
Labor market programs, the discouraged-worker effect, and labor-force participation*

1 Introduction

Sweden's labor-force participation rate (the number of persons in the labor force relative to the number of persons in the working age population) decreased sharply in the 1990s, from on average 84 % during the late 1980s to 79 % in the 1990s. This decrease in the participation rate occurred while the unemployment rate, measured in terms of the working age population, increased from on average 2 % to almost 6 %. A large increase in the number of persons participating in labor market programs paralleled the rise in unemployment. The number of participants in labor market programs in relation to the working age population rose from around 1 % in the late 1980s to more than 3 % in the 1990s.

Part of the large increase in labor market programs has been evaluated, see the overview by Calmfors, Forslund, and Hemström (2002). Most evaluation studies use micro-data and analyze if labor market programs affect future wages or the participants probability of getting a job. A few studies analyze the macro economic consequences of labor market programs, as their effect on labor demand, wages and labor supply. For example, Dahlberg and

*I am grateful to Kenneth Carling, Matz Dahlberg (Uppsala University), Anders Forslund, Erik Mellander, and Magnus Wikström (Umeå University) for comments and suggestions. I also thank seminar participants at IFAU, the Department of Economics at Uppsala University, and participants in the Labor Economics and Policy Evaluation workshop in Uppsala 2001. This paper was presented at the EEA conference in Lausanne 2001. Another version of the paper was presented at the conference "What are the effects of labor market policy" in Stockhom 2001.

Forslund (1999) find significant direct displacement effects on regular employment from use of labor market programs. The results in Forslund and Kolm (2000) indicate that the number of persons in labor market programs does not affect wage setting. This study focuses on effects of programs on labor supply. This question has become more important in recent years, when labor shortage has been a problem - not high unemployment as in the early the 1990s. One positive effect of labor market programs is that they could prevent labor force outflow, which could be important as Sweden's labor force is expected to decrease, because of the demographic structure.

Labor market programs may affect the labor-force participation in several ways: (1) programs could affect income of the unemployed. For some programs, program participants are paid more than the unemployment benefits; (2) programs could result in a higher job-offer probability, by, for example, affecting participants qualifications and thus increasing future income; (3) programs have been used to qualify for new periods of unemployment benefits. Taken together, programs could increase labor-force participation, because they directly or indirectly could increase income and thus the value of labor-force participation. Labor market programs have been used extensively in Sweden, so their effect on participation could be non-negligible.

labor-force participation data have a clear pattern, where changes in the participation rate are strongly and positively correlated with changes in employment, which indicates strong business-cycle variation in the participation rate. Flows between nonparticipation and employment are also pro-cyclical. Business-cycle variation in real wages in Sweden is relatively small, so shocks to real wages could not be the only explanation behind pro-cyclical movements of the participation rate. The discouraged-worker effect is a candidate for explaining business-cycle fluctuation in the participation rate. According to the discouraged-worker effect, the participation rate will decrease when it is difficult to get a job and increase when it is easy to find a job so that people move in and out of labor force - depending on the state of the business cycle. Labor market programs can reduce variation in labor-force participation that is due to the discouraged-worker effect because programs are typically counter-cyclical.

Empirical studies indicate that the discouraged worker effect is present. The effect of labor market programs on labor-force participation has not been studied internationally, but some attempts were made on Swedish data. Using Swedish time series data, Wadensjö (1993) finds that unemployment and labor market programs affect the change in labor-force participation. Labor market programs have a positive effect and unemployment has a negative effect on labor-force participation. He concludes that more studies must be done because the estimated sizes of the effects are sensitive to the specification and to the included trend term in the equation. Using Swedish time series data, Johansson and Markowski (1995) estimate an equation for the change in labor-force participation rate with the change in regular employment and the change in labor market programs - divided by the change in the working-age population. Both employment and labor market programs have a positive effect on labor-force participation. Dahlberg and Forslund (1999) estimate direct displacement effects of labor market programs in Sweden, and their results indicate that labor market programs are increasing labor-force participation, because the estimated displacement effect is larger when employment is divided by labor force than when divided by population. Taken together, empirical results on Swedish data indicate that the state of the business cycle and labor market programs have effects on labor-force participation.

This paper estimates the macro-economic effect of labor market programs on labor-force participation. Swedish empirical results, regarding the effect of labor market programs on labor-force participation, are either obtained indirectly, as in Dahlberg and Forslund (1999), or obtained using time series data. In this study, the focus is on effects on the participation rate during the extreme labor market situation in the 1990s. The data set is richer than those used by Johansson and Markowski (1995) and Wadensjö (1993), and instrument variables are used in the estimation.

The rest of the paper is organized like this: Section 2 presents the theoretical background for the estimations. Section 3 contains a description of the data, and Section 4 contains the empirical results. Section 5 presents a discussion of the results.

2 Theoretical model

This section presents a theoretical model for labor force determination. The model is used to determine which variables should be included in the estimation and to determine their expected effects on labor-force participation. An individual will participate if the value of participating in labor force is larger than the value of non-participation. Participants in labor force could be employed, open unemployed or participate in a labor market program. Non-participants are for example students, part-time pensioner, or people that for other reasons chose to stay outside the labor force.

2.1 The model

The theoretical model is a search model with endogenously determined labor-force participation, based on Calmfors and Lang (1995), Holmlund and Lindén (1993), and Pissarides (1990). The same model is used in Essay II in Johansson (2006). In the model, the labor-force participation decision is based on a comparison between the value of participation and non-participation. Labor force participants can flow between three different labor market states. The factors determining the flows between the states are described, and the discounted values of being in each state are calculated. The parameter restrictions needed to ensure that regular employment is preferred to other states are presented before the effects on the labor-force participation rate are calculated. The theoretical model is slightly reformulated to correspond to the empirical measures available.

2.1.1 The states and flows in the labor market

Figure 1 describes states and flows in the labor market. The number of persons in each state is expressed in terms of the working-age population, and the population is assumed to be fixed. Labor force participants may be employed, e, openly unemployed, u, or participating in labor market programs, r, and $e+u+r=1$. The states and the flows for participants are the same as in Holmlund and Lindén (1993). Non-participants flow in and out from the labor force via open unemployment. The instantaneous flow rates in and out from non-participation depend on the realization of η and they are denoted ψ and ξ, respectively. It is assumed that all non-participants who want to participate in labor force have to be openly unemployed job seekers before moving to employment. This assumption is relaxed in the empirical analysis.

The job separation rate is denoted ϕ and represents exogenously given negative shocks to firms that result in reduced regular employment. A fraction $(1-\mu)$ of the number of persons that are separated from a job become unemployed, and a fraction μ is placed in a program. The probability of entering a program if openly unemployed is γ, and the probability of becoming unemployed after program participation is λ.

The firms are creating vacancies, and the openly unemployed and participants in labor market programs search for vacant jobs.[1] The number of matches depends on the number of vacancies and on the number of searchers, that is, the number of openly unemployed and participants in labor market programs. Increased labor market tightness, θ, (the number of vacancies divided by the number of searchers) increases the probability of getting a job

[1] There is no on-the-job search in the model.

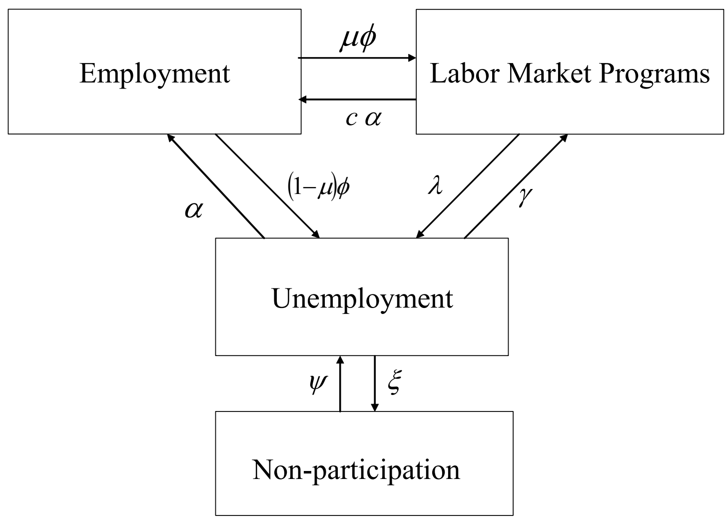

Figure 1: The states and flows in the labor market

offer, $\alpha(\theta)$.[2]

The probability of getting a job differs between the unemployed and the participants in labor market programs; the c parameter captures this difference. If c is greater than one, labor market programs have positive effects on the job-offer probability for the program participants compared to the openly unemployed. If c is less than one, program participants have smaller chances of getting a job offer than the openly unemployed. One reason could be that program participants search less than openly unemployed.

[2]To see this, assume that the number of hirings is determined by $h = h(s, v) = h(cr + u, v)$. The number of effective searchers, $s = cr + u$, and the number of vacancies, v, increase the matching function. Assume that all hirings come from the stock of searchers, $h = \alpha s = \alpha(cr + u)$. Then, the job offer arrival rate is $\alpha = h/s = h(s, v)/s$. If constant returns to scale are assumed for the h-function, we can express the job offer probability α as a function of labor market tightness, $\theta = v/s$. With constant returns to scale $\alpha = h(s, v)/s = h(1, v/s) = h(1, \theta) = \alpha(\theta)$, where $\theta = v/s$ is the labor market tightness. The job-offer probability α is increasing with labor market tightness θ.

2.1.2 The labor-force participation decision

People in the working-age population choose to participate in the labor force if the value of participating is greater than the value of non-participation. More people will participate in the labor force if the value of participation is increased. When out of labor force, non-participants benefit from for example the value of leisure, the value of education or the value of other activities they are engaged in. Working hours are assumed to be fixed, so only full-time jobs are considered.[3]

The value of non-participation, $\delta\Lambda_{np,i}$, consists of two parts: (1) $f(z)$, that describes the impacts of variables outside the theoretical model, for example age, number of children and the supply of day-care services; (2) and η_i, a stochastic shock to preferences, which is uniformly distributed between $\eta_{\min}$ and $\eta_{\max}$. δ is the discount factor. The value of non-participation for an individual is

$$\delta\Lambda_{np,i} = f(z) + \eta_i. \tag{1}$$

η_i is the realization of the individual-specific shock. The labor force participant who is indifferent between labor-force participation and non-participation has $\delta\Lambda_{np,i} = \delta\Lambda_u$, where Λ_u is the value of being an unemployed job searcher and δ the discount factor. In the theoretical model, it is assumed that all non-participants who want to participate in labor force have to be openly unemployed job seekers before moving to employment.[4] The cut-off value, η_*, for the marginal participant is given by

$$\eta_* = \delta\Lambda_u - f(z). \tag{2}$$

The participation rate is the integral of the density function for η up to the cutoff value, which takes the following expression when η_i is uniformly distributed:

$$\int_{-\infty}^{\eta_*} \frac{1}{\eta_{\max} - \eta_{\min}} d\eta = \frac{\eta_* - \eta_{\min}}{\eta_{\max} - \eta_{\min}} \tag{3}$$

The participation rate is the proportion of the working age population that has a value of η_i up to η_*. Substitute the expression for η_* in equation (1) in equation (3) to express the participation rate as a function of the variables in the model:

[3]The reason for not allowing labor force participants to vary their labor supply is that data on the number of hours worked are not available in the dataset, so we cannot empirically distinguish between full-time and part-time workers.

[4]This assumption is relaxed in the empirical analysis.

$$\frac{lf}{pop} = \frac{\delta\Lambda_u - f(z) - \eta_{\min}}{\eta_{\max} - \eta_{\min}}. \tag{4}$$

The participation rate depends positively on the discounted value of being a job seeker, $\delta\Lambda_u$. The effect of $f(z)$ on the participation rate is assumed to be negative[5]. To summarize, the model predicts that the participation rate increases in the same variables that increase the value of being an unemployed job seeker, Λ_u.

2.1.3 The value of the states for labor force participants

The discounted value of the different states (employment, $\delta\Lambda_e$, open unemployment, $\delta\Lambda_u$, and program participation, $\delta\Lambda_r$) is computed as the discounted income in each state - accounting for the probability of changing state and the income in the new state.

$$\delta\Lambda_e = [w + (1-\mu)\,\phi\,(\Lambda_u - \Lambda_e) + \mu\phi\,(\Lambda_r - \Lambda_e)] \tag{5}$$

$$\delta\Lambda_r = [\rho_r w + c\alpha\,(\Lambda_e - \Lambda_r) + \lambda\,(\Lambda_u - \Lambda_r)] \tag{6}$$

$$\delta\Lambda_u = [\rho_u w + \alpha\,(\Lambda_e - \Lambda_u) + \gamma\,(\Lambda_r - \Lambda_u)] \tag{7}$$

Employed workers earn w and the conditional probabilities of open unemployment or participation in a program are $(1-\mu)\,\phi$ and $\mu\phi$. Participants in labor market programs earn $\rho_r w$ and they become employed or openly unemployed with probabilities $c\alpha$ and λ. Openly unemployed earn $\rho_u w$, and they become employed or placed in a labor market program with probabilities α and γ. Equations (5)-(7) are used to calculate the value of the states

[5]If Λ_u and $f(z)$ contain the same variables, it is assumed that the positive effect of variables in Λ_u is small in relation to the negative effect of $f(z)$. In a model with an endogenously determined value of leisure, the value of leisure depends on parameters in the utility function. The value of leisure will be an increase in wealth; a variable that could be affected by the same variables as Λ_u. It is assumed that possible effects of wealth are small.

for labor force participants.[6]

An unemployed person accept job offers if the value of employment is greater than or equal to the value of being unemployed, $\Lambda_e \geqslant \Lambda_u$. The condition is:

$$\mu\phi\left(\rho_r - \rho_u\right) \leqslant \gamma\left(1 - \rho_r\right) + \left(\delta + \lambda + c\alpha\right)\left(1 - \rho_u\right) \tag{8}$$

This condition is likely to be satisfied for normal parameter values, where $\rho_u \leqslant \rho_r \leqslant 1$, because $\mu\phi$, the flow rate from employment to labor market programs, is small compared to the other rates in the expression. Furthermore, the difference $(\rho_r - \rho_u)$ is presumably smaller than $(1 - \rho_r)$ and $(1 - \rho_u)$. If the levels of the replacement rates are restricted, so that the replacement rate is the same for program participants and openly unemployed, $\rho_r = \rho_u = \rho$, the condition in (8) is satisfied if $\rho \leqslant 1$.

Program participants accept a job offer if the value of employment is greater than the value of participating in a program, $\Lambda_e \geqslant \Lambda_r$. The condition is:

$$\phi\left(1 - \mu\right)\left(\rho_r - \rho_u\right) \leqslant \left(\alpha + \gamma + \delta\right)\left(1 - \rho_r\right) + \lambda\left(1 - \rho_u\right) \tag{9}$$

This condition is likely to be satisfied for realistic values of the replacement rates, $\rho_u \leqslant \rho_r \leqslant 1$, because the flow rate from employment to open unemployment, $\phi(1 - \mu)$, has to be smaller than the sum of the flow from open unemployment to employment, α, the flows rates between unemployment and program participation, γ and λ, and the discount factor, δ. The condition could be violated if the difference between the replacement rates is large enough. For the special case when $\rho_r = \rho_u = \rho$, the condition in (9) is satisfied if $\rho \leqslant 1$.If $\rho_u < \rho_r = 1$, the condition in (9) is satisfied if $\phi(1 - \mu) \leqslant \lambda$, so the flow from employment into unemployment must be smaller than or equal to the flow from programs into unemployment.

[6] The expression for the values of the states are the following:

$$\begin{aligned}
\Lambda_e &= w\left(\delta\Delta\right)^{-1}\{[\phi\left(\left(1-\mu\right)\left(\delta + c\alpha\right) + \lambda\right)]\rho_u + [\phi\left(\mu\left(\alpha+\delta\right)+\gamma\right)]\rho_r + \\
&\quad +\delta\left[\delta + \alpha\left(c+1\right) + \gamma + \lambda\right] + \alpha\left[\lambda + c\left(\gamma+\alpha\right)\right]\} \\
\Lambda_r &= w\left(\delta\Delta\right)^{-1}\{[\delta(\gamma+\delta+\alpha+\phi) + \phi(\gamma+\mu\alpha)]\rho_r + \\
&\quad +[\phi(\lambda + c\alpha(1-\mu)) + \delta\lambda]\rho_u + \alpha[c(\alpha+\delta+\gamma)+\lambda]\} \\
\Lambda_u &= w\left(\delta\Delta\right)^{-1}\{[\left(\delta+\phi+\lambda+c\alpha\right)\delta + \phi(c(1-\mu)\alpha+\lambda)]\rho_u + \\
&\quad +[\phi(\gamma+\mu\alpha)+\delta\gamma]\rho_r + [\delta + c(\gamma+\alpha)+\lambda]\alpha\} \\
\text{where } \Delta &= \left(\delta + c\alpha + \lambda\right)\left(\delta+\phi+\alpha\right) + \gamma\left(\delta+\phi+c\alpha\right) + \left(1-c\right)\alpha\mu\phi.
\end{aligned}$$

An unemployed person accepts a place in a program if the value of participation in a program is greater than the value of being openly unemployed, $\Lambda_r \geqslant \Lambda_u$. The condition is:

$$(\phi + \delta)(\rho_r - \rho_u) \geqslant \alpha((1 - \rho_r) - c(1 - \rho_u)) \tag{10}$$

When $\rho_r = \rho_u < 1$, the condition in (10) is satisfied if $c \geqslant 1$. The parameter c captures all differences in the probability of getting a job-offer between program participants and openly unemployed. The job-offer probability for program participants has to be at least as large as for openly unemployed, because the replacement rates, and therefore income, are the same. On the other hand, if $c < 1$, program participants have to be compensated for the reduced probability of getting a job, so $\rho_r > \rho_u$. Involuntary flows from unemployment to programs could be observed, because unemployed people could be forced to participate in programs in order to retain their benefits. In such cases, the self-selection constraint in (10) is not fulfilled. Note that if programs are used to qualify the unemployed for new periods of unemployment benefits, it would increase the value of Λ_r, and relax the constraint in (10). This effect of programs is not included in the model. Taken together, the self-selection constraints imply that $\Lambda_e \geqslant \Lambda_r \geqslant \Lambda_u$. Restrictions on the policy parameters, $\lambda, \gamma, \mu, \rho_r$, and ρ_u are needed to satisfy the selection constraints.

2.1.4 Reformulation of the model to correspond to empirical measures

The labor-force participation rate depends positively on the value of being a job seeker, Λ_u, see equation (4), implying that new participants enter open unemployment. Empirically, we observe flows between non-participation and all three states of labor-force participation. Unfortunately, data do not cover all job seekers, only unemployed persons who are registered at an employment office are covered.

The theoretical model could be slightly reformulated to correspond to the empirical measures. Let the cutoff value, in (2), be $\eta_* = \delta\Lambda_e - f(z)$, then the participant who is indifferent between participation and non-participation has $\delta\Lambda_{np} = \delta\Lambda_e$, - in other words the value of non-participation is equal to the value of employment. The new entrants could then enter regular employment. For the purposes of of the model in this paper, it does not matter which state non-participants enter, because the values of the different states react in the same direction to the same shock, see Table *1*.

2.2 The effects on the labor-force participation rate

The way in which the values of the states in the labor market and the participation rate are affected by changes in the model's parameter is displayed in Table 1. Λ_e, Λ_r, Λ_e are the discounted values of the expected income in the different states for labor force participants, employment, labor market programs, and open unemployment.

Table 1: Effects on the labor-force participation rate

Increase in	**Effect on**				
	Λ_u	Λ_r	Λ_e	participation rate	
w, wage	+	+	+	+	
ρ_r, ρ_u, replacement rates	+	+	+	+	
γ, rate u to r	+	+	+	+	if $\Lambda_r - \Lambda_u \geqslant 0$
λ, rate r to u	-	-	-	-	if $\Lambda_r - \Lambda_u \geqslant 0$
μ, share from e to r	+	+	+	+	if $\Lambda_r - \Lambda_u \geqslant 0$
c, relative eff of program	+	+	+	+	if $\Lambda_e - \Lambda_r \geqslant 0$
ϕ, rate from e to u and r	-	-	-	-	if $\rho_r, \rho_u \leqslant 1$
$\alpha(\theta)$, rate from u and r to e	+	+	+	+	

An increase in wages, w, increases the value of participation and thus increases labor-force participation. ρ_r and ρ_u are the replacement rates (income as a fraction of earnings) during program participation or unemployment. Higher replacement rates increase the value of labor-force participation in the same way as higher wages.

Increased inflows into programs, γ, and increased shares of laid-off workers who enter directly into labor market program, μ, have positive effects on labor-force participation if the value of participating in a program is larger than being openly unemployed, that is, if $\Lambda_r - \Lambda_u \geqslant 0$. And increased outflow rates from programs into unemployment, λ, have negative effects if $\Lambda_r - \Lambda_u \geqslant 0$.

The self-selection constraint, $\Lambda_r - \Lambda_u \geqslant 0$, in (10) is fulfilled if the income for program participants is larger than for openly unemployed. This has been the case for some programs. Often, participants in job-creation programs are paid more than the unemployment benefit, while participants in training programs receive the unemployment benefit. If the income for unemployed and program participants is the same, labor-force participation is increased if $c \geqslant 1$, so that program participants have a greater probability of getting a job then open unemployed persons.[7] The parameter c could decrease during participation in some programs. It is, for example, natural to terminate a training program before searching for a new job. Naturally, the time left for job search is less when participating in full-time programs. If $c < 1$, the program's participants have to be compensated by a larger income compared with the openly unemployed.[8] Furthermore, if programs are used to qualify for new periods of unemployment benefits, the value of programs relative to open unemployment increases, and the restriction, $\Lambda_r - \Lambda_u \geqslant 0$, is eased. The selection constraint $\Lambda_r - \Lambda_u \geqslant 0$ has to be fulfilled in order to determine the sign of the effect on labor-force participation from increased probabilities of moving between open unemployment and labor market programs, γ and λ. If laid-off workers have an increased probability of participating in a program instead of becoming openly unemployed - an increase in the parameter μ in the model - the labor-force participation rate will increase if $\Lambda_r - \Lambda_u \geqslant 0$.

In the model, an increase in the relative effectiveness of programs, c, directly increases the probability of moving from programs to employment. If c increases, the participation rate is expected to increase, if $\Lambda_e - \Lambda_r \geqslant 0$ because the probability of finding a job and receiving a higher income has increased. The condition, $\Lambda_e - \Lambda_r \geqslant 0$, is likely to be fulfilled for normal parameter values, see the discussion of equation (9).

Labor market tightness, $\theta = (v/(u + cr))$, the number of vacancies divided by the number of effective job-searchers, affects the flow rates from unemployment and labor market programs into regular employment. An increased number of vacancies, v, increases the probability of finding a job and is expected to have a positive effect on labor-force participation. Increased numbers of openly unemployed persons, u, or program participants, r, increase the number of persons searching for jobs and, for a given number of vacancies and a given relative effectiveness of programs, c, it is now more difficult to find a job. The job-offer probability, $\alpha(\theta)$, depends on labor market tightness, (θ), which gives rise to the discouraged-worker effect in the model because labor market tightness is pro-cyclical.

An increased job separation rate, which is a negative employment shock, ϕ, increases the probability of being openly unemployed. This is expected to have a negative effect on the labor-force participation rate because the probability of recieving a reduced income has increased since unemployment benefits are lower than wages.

[7] Remember that c captures all differences in job-offer probabilities between openly unemployed, and participants in labor market programs.

[8] Of course, the compensation could be a combination of higher expected probability of getting a job offer and an anticipated higher wage after the program.

To summarize, we expect the following variables to affect labor-force participation rate: the wage, w, the replacement rates, ρ_r and ρ_u, the flow rates from open unemployment to programs, γ, and from programs to open unemployment, λ, the share of negative employment shocks to program, μ, the relative effectiveness of programs, c, the flow rates from employment to open unemployment, $(1-\mu)\,\phi$, and from employment to program, $\mu\phi$, and the flow rate from open unemployment to employment, $\alpha\left(\theta\right)$.

3 Data

The dataset is a panel consisting of November observations, between 1986 to 1998, for Sweden's municipalities. The dataset includes 3 692 observations (13 years times 284 municipalities) on employment, unemployment, number of program participants, vacancies, income and the job destruction rate. Description of the dataset, summary statistics and plots of the data are given in Appendix A.

The time variation is larger than the variation between the municipalities for vacancies, open unemployment, and the job destruction rate, see the summary statistics presented in Table 9 in Appendix A1. The plots of data in Appendix A2 show that the labor-force participation rate declined dramatically, from around 0.89 in 1990 to 0.83 in 1993. The real income is increasing during the sample period. The vacancy rate has a peak in 1988, and it has in 1998 not recovered after the decrease in 1990-91. The unemployment rate, measured as the number of openly unemployed divided by the number of persons in the working age population, fluctuates around two percent up to 1990, increased dramatically and reached more than eight percent in 1993. The two last years in the sample, the unemployment rate has decreased to around six percent. The use of labor market programs in the downturn of the economy when unemployment was high, is illustrated in Figure 6. The share of the working age population that was participating in labor market programs was slightly above one percent during 1986-90, and increased up to more than four percent between 94-97. The accommodation ratio, the number of participants in labor market programs divided by the number of job searchers (the sum of open unemployed and program participants) is on average around 0.63, and the variation in the accommodation ratio is larger in the beginning of the sample. The job destruction rate is on average 0.11 percent and reached a peak in 1992 with 0.17 percent.

3.1 Definition of variables

The theoretical model predicts for example that wages, labor market tightness, replacement rates, and the flow rates between the different states should affect labor-force participation, see Table 1 The flow rates are not available in the dataset, so stocks, the number of openly unemployed and participants in labor market programs have to be used instead. More details about the data are found in Appendix A

The number of persons in the labor force is calculated as the sum of the number of persons employed, unemployed and in labor market programs. Nonparticipants are the working age population, ages 18-65, excluding those in the labor force. With this definition, all participants in labor market programs are in the labor force.[9] Employment, e, is measured as the number of employed in November divided by the working age population. Unemployment, u, is measured as the number of open unemployed that are registered at an employment office divided by the working-age population. Program participants, r, is the number of jobseekers that are registered at an employment office and participating in a labor market program. The measure of unemployment is different from labor force surveys, where individuals who search actively are regarded as unemployed.[10] The number of persons registered at an employment office is somewhat smaller than unemployment according to labor force surveys. The aggregate time series variation is almost the same for the two definitions of unemployment, however. The overall wage, w, is measured by the real average annual labor income, among the employed, in each municipality.

The constant returns to scale assumption of the hiring function, see note 5, $h(v, cr + u)$, implies that the job offer probability could be expressed as a function of tightness, $\alpha(\theta) = \alpha(v/cr + u)$. The constant return to scale restriction is not imposed in the estimation because the number of effective searchers is not observable since data on c are not available. Vacancies, v, open unemployment, u, and program participants, r, are therefore included separately. Vacancies, v, is measured by the total number of vacancies reported to the labor market office divided by the working-age population. The empirical measure of the number of vacancies covers only a part of the total number of vacancies, because not all vacant jobs are reported to the labor market office.

The parameters in the theoretical model, γ, μ, and λ, describe flows into

[9] This is a difference compared to labor force surveys, where participants in some programs are defined as students and thus outside labor force.

[10] Active search means that contact with an employer should have been taken during the last four weeks.

and out from labor market programs. Data on gross flows are not available; data on stocks are used in the estimation. Therefore, it is not possible to separate positive effects of inflow into programs from negative effects of outflow from programs, because the flow parameters are summarized by the stock. In general, there is no simple one- to- one correspondence between the stock and the flow parameters in the theoretical model. For example, the steady state expression for the stock of participants in labor market programs is $\phi e \frac{\gamma+\mu\alpha}{\alpha(\lambda+c\alpha+\gamma c)}$, where e is employment. It is possible to generate a simple relation between the stocks and the flows where the accommodation ratio, the number of program participants divided by the number of searchers, could be interpreted as the probability of being placed in a program. The accommodation ratio is not used in the estimation because strong restrictions on the flows in and out from labor market programs are needed together with the assumption that $c = 1$, implying that the probability of getting a job-offer is the same for openly unemployed and labor market program participants.[11] The number of program participants divided by the working-age population, r, excluding participants in programs directed towards people with disabilities, is used in the estimation. The number of participants in labor market programs captures two effects: (1) one direct positive effect because the value of labor market participation increases with the number of persons in programs[12]; and (2) one indirect negative competition effect through $\alpha(\theta)$, the probability of getting a regular job. An increased number of participants in labor market programs will increase the number of searchers, which will have a negative competition effect for a given number of vacancies.

The negative shock to employment, ϕ, is measured by the job destruction rate. The job destruction is defined as the absolute sum of negative employment changes in the plants in each municipality. The job destruction rate is calculated as job destruction divided by average employment at each plant in period t and *t-1*. Negative employment changes are not a perfect measure of job destruction; if the number of unfilled vacancies is increased temporarily,

[11] If inflow rates into programs are the same for openly unemployed and employed, $\gamma = \mu = \varphi$, and if the probability of getting a job-offer is the same for openly unemployed and labor market program participants, $c = 1$, the accommodation ratio, $r/(r+u)$, could be written as $\varphi\frac{1+\alpha}{\varphi+\lambda+\alpha}$. Restrictions on the outflow rate from programs, λ, are needed to obtain a simpler expression. The probability of remaining in the program state, given the job offer rate, could be restricted to be the same as the probability of entering the program state, $1-\lambda = \varphi$. That is, the probability of getting a place in a program is the same for unemployed, employed, and program participants. Then, the accommodation ratio $r/(r+u)$ is equal to the flow parameter φ, and the accommodation ratio could be interpreted as the probability of being placed in a program.

[12] The value increases with the inflow rate from open unemployment and decreases with the outflow rate from programs to open unemployment.

it is counted as a negative change in employment; full time jobs and part time jobs can not be separated; job flows within one year and substitution between jobs with different positions within the plant are not considered in the calculation. Data on replacement rates, ρ_r and ρ_u, are not available at the municipality level. So time dummies capture the effect of unemployment benefits. The effectiveness parameter, c, and the discount factor, δ, are also unobservable, and captured by the time dummies.

Some demographic variables are also included in the estimation. They are assumed to have negative effects on the participation rate, and they are included in the z-vector, see equation (**??**). These variables are the number of persons between ages 18-24 and 55-65, in relation to the number of persons in the working age population, ages 18-65. These age groups have lower participation rates than the average, which reflects the number of students among the younger and that the likelihood of early retirement and sickness pensions increases with age.

The labor force, vacancies, unemployment, and the number of persons in labor market programs are divided by the lagged number of persons in the working-age population $(pop1865)_{t-1}$ instead of current population, to account for the fact that the explanatory variables could affect migration between the municipalities. For example, if the number of vacancies increases both labor force and population in the municipality, the estimated effect on the participation rate will be lower than the effect on labor force, because population is also increased. If migration is affected, the estimated coefficients will be a mixture of two effects when the variables are divided by current population, because both the numerator and the denominator of the dependent variable are affected. The demographic variables are divided by the current working-age population, and they are included lagged one period. All variables, except the demographic ones, are measured in November each year. The demographic variables are based on the population in the municipalities in December each year. *Table 2* summarizes definitions of the variables in the estimations and the expected effects on the participation rate.

4 Empirical results

The labor-force participation rate is the dependent variable in the estimation, and it is allowed to be affected by wages, vacancies, open unemployment, participants in labor market programs, the job destruction rate and the number of persons between ages 18-24 and 55-65. The model is formulated in steady state and lagged variables are included in the estimation to allow for time to

Table 2: Variable definitions

Variable	Definition	Effect
lf	number of persons in labor force$_t$/pop1865$_{t-1}$	
w	real annual income for employed$_t$	+
v	number of vacancies$_t$/pop1865$_{t-1}$	+
u	number of unemployed$_t$/pop1865$_{t-1}$	-
r	number of persons in labor market programs$_t$/pop1865$_{t-1}$	+
jdr	job destruction rate$_t$	-
$p1824$	number of persons 18-24 year$_t$/pop1865$_t$	-
$p5565$	number of persons 55-65 year$_t$/pop1865$_t$	-

adjust the labor-force participation.[13] Therefore, the expected effects from the theoretical model refer to the long run effects in the empirical model. The estimated dynamic panel data model takes the form:

$$
\begin{aligned}
lf_{i,t} \quad = \quad & \sum_{j=1}^{j=p} a_{1j} lf_{i,t-j} + \sum_{j=0}^{j=p} a_{2j} w_{i,t-j} + \sum_{j=0}^{j=p} a_{3j} v_{i,t-j} + \\
& \sum_{j=0}^{j=p} a_{4j} u_{i,t-j} + \sum_{j=0}^{j=p} a_{5j} r_{i,t-j} + \sum_{j=0}^{j=p} a_{6j} jdr_{i,t-j} + \\
& + a_7 p1824_{i,t-1} + a_8 p5565_{i,t-1} + k_i + k_t + \varepsilon_{i,t},
\end{aligned}
\tag{11}
$$

where k_i is an unobserved municipality specific effect, and k_t is a time-varying aggregate effect. The model is differenced before estimation, allowing all variables to be correlated with the unobserved municipality specific fixed effect, k_i.

The demographic variables are assumed to be exogenously determined. The economic variables could be endogenously determined, in the main through the definition of the labor force as the sum of employed, openly unemployed and participants in labor market programs. An IV-estimator is also needed because of the lagged dependent variable. The GMM estimator for dynamic panel data models suggested by Arellano and Bond (1991), is used in the estimation.[14] Endogenous variables in levels in *t-2* or earlier are valid instruments for the model in differences.

[13]The expression for the participation rate is a long, complicated, nonlinear function of the variables in Λ_e. The estimated dynamic model could be interpreted as a linear approximation of the participation rate.

[14]The main alternative is to use the extra instrument implied by the SYS-estimator. This

Lagged economic variables and current and lagged demographic variables are used as instruments in the estimation. Actually, the rules for how Sweden's Labor Market Board allocates money to the local level imply that lagged unemployment and lagged number of program participants affect spending on labor market programs, see the discussion in Dahlberg and Forslund (1999). So, use of lagged variables as instruments for the policy variable (the number of participants in labor market programs) is justified by the allocation of spending. One extra instrument that captures municipality-specific employment shocks is used in the estimation. Each industry share of employment in each municipality is calculated. Then, the average aggregate change in employment at each two-digit industry level is applied to the industry share of employment, lagged two periods.

4.1 Estimation results

First, to determine the number of lags, p, in the dynamic model in equation (11), a tentative model was estimated. The number of lagged levels of the variables that are used as instruments in the estimation of the tentative model were set to $t-2$ up to $t-4$.[15] Lags from zero, $p=0$, up to four, $p=4$, were tried for the economic variables. The demographic variables are included in $t-1$. The number of lags in the tentative dynamic model where determined as the model with the smallest number of lags that are accepted by the correlation tests. The correlation tests are the m_1 and m_2 statistics, suggested in Arellano and Bond (1991), and they indicate that the smallest number of lags in the dynamic model is two, $p=2$. The final number of lagged levels of the variables that are included in the instrument matrix were determined in the tentative model as the smallest number of instruments where the Sargan statistic accept the model.[16]

A preliminary model with $p=2$ for the economic variables was estimated. The demographic variables are included lagged one period. Insignificant coefficients in the preliminary model were deleted and a reduced model was estimated. The main estimation results are not sensitive to the chosen num-

estimator is suitable in small sample if the data is persistent. Wages is the only variable that could be persistent in this dataset, see the discussion of alternative estimators in Appendix C.

[15]The results of Sargan tests indicate that only a very small number of instruments are needed in the estimation.

[16]The difference Sargan is not used to determine the number of instruments, because it is difficult to reject a null of a too large instrument matrix. With a large instrument matrix the risk of overfitting is large and the estimator will tend to the WG estimator. Therefore, a conservative approach is taken, and the number of instruments are choosen to be as small as possible.

ber of lags and are not affected to the choice of instrument matrix, see the sensitivity analysis in Appendix C.

Table 3 presents the estimation results for the preliminary and the reduced model. The reported standard errors and p-values for the second-step estimation, are calculated with the small sample correction suggested by Windmeijer (2000).[17] Time dummies and a constant are included in the model. The estimation period is 1989-1998. The estimation results for the first-step estimation and the coefficients on the time dummies are found in Appendix B.

First we can note that the Sargan statistic and the correlation tests accept the model, and that the estimated coefficients and standard errors are almost the same in the first- and second-step estimation. Insignificant variables, at the 10 % level, were then deleted from the preliminary model. Lagged vacancies are kept because the p-value in the first-step estimation is lower than 10 %. The zero-restrictions in the preliminary model that is implied by the reduced model is not rejected by a formal test. The p-value for a Wald test of the hypothesis of zero coefficients on the variables that are deleted from the preliminary model is 0.402 in the second-step estimation.

First we can note that the second lag of the dependent variable is insignificant, but it is included because otherwise the AR(2) test indicates serial correlation. The estimated adjustment coefficient is 0.60.[18] As expected, the effect of the wage is positive.[19] The number of vacancies enters lagged one period, and as expected the effect is positive. The estimated contemporaneous coefficient on unemployment is positive, while the lagged and long run effects are negative. According to the theoretical model, which is formulated in steady state, the effect of unemployment is expected to be negative. Possible explanations for the strange immediate effect of open unemployment is

[17]The instrument matrix contains the endogenous variables at time *t-2* up to *t-4*, the exogenous demographic variables at t up to *t-4*, and the aggregate employment shock at t. This is the smallest number of lagged endogenous variables as instruments that is accepted by the Sargan statistic. The package DPD for Ox, see Doornik, Arellano, and Bond (2001), is used in the estimation. The correlation tests are the m_1 and m_2 statistics, suggested in Arellano and Bond (1991). The differencing of the model, due to the fixed effect, will introduce a moving average error. Therefore, the AR(1) test should indicate correlation, while the AR(2) test should not. It is assumed that enough lags are included in the level equation, which is assumed to have uncorrelated errors.

[18]The adjustment coefficient is calculated as one minus the sum of coefficients on lagged participation rate, which is (1-0.361-0.035). The long run effect of a variable is calculated as the sum of the coefficients on the variable divided by the adjustment coefficient.

[19]Note that the preliminary model indicate that it could be the change and not the level of the real wages that matters, because the estimated coefficients on lagged wages is the same as on current wages but with reversed sign.

Table 3: Estimation results, second step estimation

	Preliminary model			Reduced model		
Variable	**Coeff**	**p-val**	**SE**	**Coeff**	**p-val**	**SE**
lf_{t-1}	0.347	0.000	0.041	0.361	0.000	0.039
lf_{t-2}	0.040	0.092	0.024	0.035	0.137	0.023
w_t	0.008	0.050	0.004	0.004	0.083	0.002
w_{t-1}	-0.007	0.126	0.004			
w_{t-2}	-0.000	0.773	0.000			
v_t	0.108	0.476	0.151			
v_{t-1}	0.137	0.117	0.088	0.176	0.042	0.086
v_{t-2}	-0.034	0.447	0.045			
u_t	0.497	0.000	0.059	0.483	0.000	0.058
u_{t-1}	-0.523	0.000	0.063	-0.547	0.000	0.056
u_{t-2}	-0.145	0.001	0.044	-0.138	0.002	0.044
r_t	0.649	0.000	0.059	0.634	0.000	0.069
r_{t-1}	-0.209	0.001	0.063	-0.212	0.000	0.059
r_{t-2}	-0.037	0.389	0.044			
jdr_t	-0.127	0.000	0.021	-0.121	0.000	0.021
jdr_{t-1}	-0.012	0.076	0.007	-0.012	0.042	0.006
jdr_{t-2}	-0.001	0.856	0.006			
$p1824_{t-1}$	-0.395	0.000	0.058	-0.409	0.000	0.057
$p5565_{t-1}$	-0.160	0.001	0.049	-0.150	0.002	0.049
Sargan	259.6	0.392		268.6	0.343	
$AR(1)$	-7.5	0.000		-8.1	0.000	
$AR(2)$	11.8	0.066		1.6	0.122	

Note: Estimation period 1989-1998, yearly data for 284 municipalities, 2 840 observation. Constant and time-dummies are included in the estimation. The model is estimated with GMM. Results from the secon step estimation are reported. Robust standard errors are used. The model is transformed into differences. The instruments that are used are the following: lf, w, v, u, r, jdr, are included at $t-2$, $t-3$, $t-4$, $p1824$ and $p5564$ are included at $t-0$ up to $t-4$, the employment shock is included differenced as an extra instrument in $t=0$. The $p-values$ are zero for Wald tests of joint significant coefficients, and joint significant time-dummies.

that too many questions are asked. Unemployment and programs are much correlated, the correlation is 0.85, and it could be difficult to separate the effects from each other empirically. The immediate effect of the number of participants in labor market programs is positive, the lagged effect is negative, and the long run effect is positive, as expected. The immediate and

Table 4: Estimation results, time-dummies, second step estimation

	Preliminary model			**Reduced model**		
Variable	**Coeff**	**p-val**	**SE**	**Coeff**	**p-val**	**SE**
const	-0.0043	0.000	0.0012	-0.0044	0.000	0.0011
$t1990$	-0.0005	0.787	0.0019	-0.0019	0.256	0.0016
$t1991$	-0.0209	0.000	0.0023	-0.0208	0.000	0.0023
$t1992$	-0.0100	0.002	0.0032	-0.0086	0.007	0.0032
$t1993$	-0.0246	0.000	0.0033	-0.0247	0.000	0.0031
$t1994$	0.0279	0.000	0.0033	0.0286	0.000	0.0032
$t1995$	0.0082	0.001	0.0024	0.0071	0.002	0.0023
$t1996$	-0.0062	0.000	0.0017	-0.0055	0.000	0.0015
$t1997$	-0.0057	0.005	0.0020	-0.0071	0.000	0.0018
$t1998$	0.0123	0.000	0.0020	0.0110	0.000	0.0017
Sargan	259.6	0.392		268.6	0.343	
$AR(1)$	-7.5	0.000		-8.1	0.000	
$AR(2)$	1.5	0.142		1.6	0.122	

Table 5: Immediate and long run effects

Variable	**Immediate**			**Long run**		
w	0.004	[0.008]	[0.002]	0.007	[0.012]	[0.003]
v	-			0.291	[0.526]	[0.056]
u	0.483	[0.579]	[0.388]	-0.332	[-0.013]	[-0.677]
r	0.634	[0.747]	[0.521]	0.699	[1.081]	[0.317]
jdr	-0.121	[-0.087]	[-0.155]	-0.219	[0.162]	[-0.601]
$pop1824$	-			-0.676	[-0.265]	[-1.087]
$pop5565$	-			-0.247	[0.225]	[-0.720]

lagged effects of the job destruction rate are negative, as expected. And the effect of the demographic variables, the proportions of persons ages 18-24 and 55-65 are negative, as expected.

Table 5 presents the immediate and long-term effects, together with 90

% confidence intervals[20]. The effect of the wage is positive and significant in both the short and long run. The long-term effect of the wage corresponds to an income elasticity of 0.049 (see *Table 6*). The long-term effect of the number of vacancies is significantly different from zero. The point estimate indicates that if the number of vacancies is permanently increased by 100, the number of participants in labor force increases by 29 persons in the long run. The estimated long-run effect of unemployment is negative (-0.33), while the estimated immediate effect is positive. If unemployment increase by 100, the number of participants in labor decreases by 33 persons in the long run. The estimated long-run effect of unemployment is about the same size as the long-run effect of vacancies with opposite sign. The estimated long-term effect of labor market programs is slightly higher than the immediate effect. If the number of participants in labor market programs is increased permanently by 100, the labor force increases immediately by 63 persons and by 70 persons in the long run. If a permanent increase in open unemployment is followed by a permanent increase in the number of program participants by 100, the total long run effect on labor force is 37. The estimation results indicate that labor market programs are reducing business-cycle variation in the labor force, because the effect is positive and programs are counter-cyclical, that is, they tend to be increased when unemployment is high, see Figure 6. The long-term effect of an increased number of participants in programs is positive, which means that some labor force participants who would have left the labor force in the absence of programs are now participating because of the programs. The estimation results suggest that if the number of participants in programs is permanently increased, it will have a relatively large effect on labor-force participation. The immediate negative effect of the job destruction rate is smaller than the long run effect, -0.12 compared to -0.22. If the number of destroyed jobs is increased by 100, 22 persons will leave labor force in the long run. The long-run effect of the job destruction rate is not significantly different from zero. And the long-run effects of the demographic variables are negative and larger than the short-run effects. The long-run effect of the proportion of 55 to 65 years old is not significantly different from zero, while the long-run effect of the proportion 18 to 24 years old is significant. To summarize, the estimated long-run effects are of the expected signs, and the largest effects are found for labor market programs and the proportion of persons between ages 18 and 24.

In the estimation, all program participants are defined as in the labor force. If instead all program participants are defined as out of labor force, the

[20] The calculation of confidence interval is based on the adjusted standard errors in the second step estimation.

implied effect of programs on regular employment and open unemployment is -0.30 in the long run. To see this, note that when r is increased with 100, the estimation result indicate that labor force increase with 70 persons. If we redefine labor force to include only open unemployed and regular employed, the effect on the new definition of labor force has to be -30 to be consistent with the estimation result.

The model is also estimated with labor market programs, r, and open unemployment, u, interacted with each other. More specifically, u_t is interacted with r_t and r_{t-1}, and u_{t-1} is interacted with r_t and $r_{t-1.}$ In both cases, the long run interaction term is positive, signaling that when open unemployment is above average, the estimated effect of labor market programs is larger. The same result is obtained when u_t, u_{t-1}, and u_{t-2} are interacted with r_t, so the negative effect on labor-force participation of increased open unemployment is reduced by labor market programs.

Table 6: Immediate and long run elasticities

Variable	**Immediate**	**Long run**
w	0.030	0.049
v	-	0.003
u	0.029	-0.020
r	0.019	0.021
jdr	-0.016	-0.029
$pop1824$	-	-0.121
$pop5565$	-	-0.052

Table 7: Effect of changes with one standard deviation

Variable	**Immediate**	**Long run**
w *(9%)*	12 196	20 226
v (46 %)	-	6 752
u (53 %)	70 333	-48 295
r (50 %)	43 325	47 744
jdr (20 %)	-14 195	-25 755
$pop1824$ (4 %)	-	-23 883
$pop5565$ (3 %)	-	-7 366

In *Table 6,* the estimates are converted into elasticities, evaluated at the mean of the variables. In general, the estimated elasticities are small. At the same time, the average percentage change in the labor-force participation rate is small too, -0.6 %. To illustrate the magnitudes of the estimated effects, an experiment is carried out, where the variables are increased permanently with one standard deviation. A one standard deviation shock is selected because it measures the size of a typical shock during the sample period. In the experiment, employment and the number of persons in the working age population are assumed to be constant. From *Table 7* we can note that the standard deviations are low for the population ratios, implying that "normal" shocks are relatively small. The standard deviations for the number of vacancies, unemployment, and labor market programs are around 50 %, which reflects the huge increase in unemployment in the early 1990s. The variation in the job destruction rate and wages are about 20 and 10 %, respectively. Results from the experiment indicate that in the long run, labor market programs and unemployment have about the same effect but with opposite signs. So programs could offset a permanent increase in open unemployment.

4.2 Alternative estimations

This section presents results from alternative estimations of the model, to examine if the estimation results are sensitive to the assumptions in the estimation. Here, it is only discussed the result for the effect labor market programs.[21] Table 8 summarize the estimated effects of labor market programs on labor-force participation for the alternative estimations.

The following potential problems are considered in the alternative estimations: *i*) The small sample performance of the estimator could be problematic if data are persistent. The model is therefore estimated with an alternative estimator that could perform better in small samples when data are persistent, which is often the case with macro-data, (*SYS-estimator* in Table 8). *ii*) All available information are not used in the estimation because only instrument dated $t-2$ to $t-4$ are used. The model is thus estimated with all available instruments to examine if the results are affected by the choice of instruments, (*all instruments used). iii*) The assumptions of constant coefficients in the time and municipality dimension are relaxed. In the estimations denoted *sample period 89-94* and *94-98* in Table 8, the sample is divided in two subperiods. *iv*) To examine if the estimation results are sensitive to the size of the population in each municipality, the model is estimated excluding municipalities with populations larger than 95 000, 50 000, and 20 000. Municipalities with populations less than 7 500, 12 500 and 15 000 are also

[21] A full presentation of the estimation results from the alternative estimations are given in Appendix C.

excluded. v) The long run effect of labor market programs is decomposed into one direct positive effect and one indirect negative effect by assigning values to the c-parameter such that the number of effective searchers could be calculated. The c-parameter is set to 0.5, 1, and 1.5 respectively and denoted $c = 1.0$, $c = 1.5$, and $c = 0.5$ in Table 8. The results from estimation where it is examined if the standard-errors are affected by the level of spatial aggregation, indicate that the significance of the estimated parameters are not affected, see the discussion in Appendix C.

Table 8: Estimated long run effect of labor market programs

	Long run effect of programs
Reduced model	0.699
90 % confidence band	[1.081] [0.317]
SYS-estimator	0.495
All instruments used	0.348
Sample period 89-94	0.752
Sample period 94-98	0.660
$Pop \leqslant 95\ 000$	0.630
$Pop \leqslant 50\ 000$	0.731
$Pop \leqslant 20\ 000$	0.694
$Pop \geqslant 7\ 500$	1.022
$Pop \geqslant 12\ 500$	0.900
$Pop \geqslant 15\ 000$	0.577
$c = 1.0$	0.683
$c = 1.5$	0.723
$c = 0.5$	0.572

Long run effect of labor market programs in the alternative estimations *Table 8* presents a summary of the estimated long run effects of labor market programs in the alternative estimations. In the reduced model, the estimated long run effect of programs is 0.70, see *Table 4*. None of the alternative estimation results in estimated long run effects that are significantly different from the one obtained in the reduced model. The point estimates are between 0.35 and 1.02, and most of the point estimates are close to 0.70. That is, the effect of labor market programs is very robust to different specifications and estimation methods. The smallest effect is obtained when the larger instrument matrix is used. The largest effect is obtained when the smallest municipalities are excluded from the model.

The estimated long run effect of open unemployment is larger when the SYS-estimator is used, positive when the model is estimated between 1994-98, and smaller when municipalities with large population are excluded. It is difficult to determine the size of the discouraged worker effect, because the size of the long run effect of open unemployment vary between some of the different estimation methods and models.

4.3 Comparison with other studies

Large effects from labor market programs are also found in other studies. Dahlberg and Forslund (1999) use the same kind of data as in this study but consider a shorter sample period. In their estimation, the implied short run effect on labor-force participation from labor market programs is around 0.60, which is about the same magnitude as results obtained here. The estimates in Johansson and Markowski (1995), who use Swedish time series data between 1970-92, indicate that a 50 % increase of the number of participants in labor market programs cause an immediate[22] increase in labor force with 27 300 persons, evaluated at the mean of the sample used here. The effect is smaller than the one obtained here, 43 000 persons; see *Table 7*. Wadensjö (1993) obtains the result that a 1 % increase in labor market programs increases labor force with slightly more than 1 %. This effect is much larger than the results obtained here, where the long run elasticity is estimated to 0.02, see *Table 6*. He notes that the sizes of the estimated effects are sensitive to the specification of the equation.

5 Discussion of the results

The estimated coefficients on labor market programs suggest that they have relatively large positive long- and short-run effects on the labor-force participation rate. The positive effects from programs are robust against different specifications, different choices of the instrument matrix, and different estimation methods. The estimated long run effects of programs in different alternative estimations are not significantly different from the one in the reduced model. Furthermore, the estimated size of the effect of labor market

[22] The long run effect from labor market programs is restricted to zero in their estimation.

programs is very robust, most of the point estimates in the alternative estimations are very close to the result in the reduced model. The size of the discouraged worker effect is more difficult to determine because the estimated long run effect of open unemployment differ in some of the alternative estimations.

The positive effects on the labor-force participation rate indicate that labor market programs reduce business-cycle variation in labor-force participation because programs are counter-cyclical. The positive long run effect of programs is larger than the absolute value of the long run effect of unemployment, so programs counteract the discouraged-worker effect. The positive effect of programs is counter-cyclical, so when open unemployment is above average, the positive effect of programs is larger. A permanent increase in the number of persons in labor market programs during a downturn in the economy could prevent people from dropping out of the labor force, because participants who would have left labor force in the absence of programs are now maybe participating because of the programs.

In practice, labor market programs have been used to qualify unemployed for new periods of unemployment benefits, which causes difficulties in interpreting estimation results. The true effect of labor market programs on the effective labor supply is probably smaller than the estimated coefficients indicate, because we do not know the extent of dropouts in absence of labor market programs used for renewal of benefits periods.[23] And it should be pointed out that the estimation results do not measure the effect of programs on the effective labor force, because we do not know if labor force participants, who choose to participate in the labor force because of labor market programs, search for jobs to the same extent as other labor force participants. If they search less, the effect on the effective labor force will be smaller than the estimated coefficient indicates. Furthermore, the estimated coefficients measure the partial effects on the labor supply, so it is impossible to conclude that an increased number of participants in labor market program is an effective way to increase labor-force participation. For this to be done, programs' costs, for example, must be accounted for.

Because labor-force participation is increasing in labor market program participation, the book keeping relation between employment, unemployment, labor market programs and labor force should not be used when forecasting the labor market situation. For example, political targets for open unemployment, which have been used in Sweden, are harder to reach by increasing the number of participants in labor market programs, because open unemployment is not reduced by the same amount.

[23] The benefits from the unemployment insurance is larger than the social allowance.

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A The data

The data set is a panel consisting of yearly observations from 1986 to 1998 for Sweden's municipalities. The dataset includes 3 692 observations (13 years times 284 municipalities). The advantage with this dataset, compared to aggregate time series, is that the extreme situation during the 1990s is covered at the same time as the time dimension is sufficiently large to capture some business cycle variation, but without having to assume that the estimated parameters are constant over a long time horizon.

Employment, population by age, and annual labor income are obtained from Statistics Sweden. Observations on employment and labor income are based on the RAMS register, and they are measured in November. Municipality population is measured at the end of December each year. Data on the number of vacancies, unemployed, and labor market program participants are obtained from the National Labor Market Board (Ams). The number of unemployed and participants in programs are available on monthly basis. The number of vacancies between 1985 and 1990 in November are obtained manually from microfiches at National Labor Market Board central archives, and from august 1991 monthly data are obtained from the National Labor Market Board. Data on employment at the plant level that are used to calculate the job destruction rate, are obtained from a database at IFAU. Employment at the plant level is only available in November.

Employment and wages are only available in November, population in December, and the other variables each month, except for the number of vacancies, which have to be obtained manually from microfiches before august 1991. November data on vacancies, employment, and labor market programs are used in the estimation. The use of November data could be problematic if the seasonal pattern differs so that observations are not representative. It is likely that the variables have approximately the same seasonal pattern because all variables are related to the labor market. Alternatively, yearly data on vacancies, unemployment and program participants could be used, assuming that November observations on employment, wages and job destruction rate are representative for the whole year. The variations in employment and wages are probably small during a year, but the variation in the job destruction rate could be large, so that November observations on job destruction rate is not representative for the whole year.

A.1 Summary statistics

Table 9 presents descriptive statistics for the variables used in the estimation. All variables are divided by the number of persons in the working-age population. The overall standard deviation is calculated using the total number of observations (3 692). The overall variability could be divided into the variability between and within the municipalities. The variation between the municipalities is calculated as the deviation of the mean over time for each municipality from the total mean. The variation within municipalities is calculated as the deviation of each observation in each municipality from the mean over time in each municipality.

The variability between municipalities is larger than the within variability for the number of persons between ages 55-65. Both the between and within variability contribute to total variance in labor force, wages, and labor market programs. The within variance is larger for vacancies, open unemployment, and job destruction rate, implying that the difference over time is larger than the difference between municipalities.

Table 9: Summary statistics of the variables in the estimations

Variable		**Mean**	**Std. Dev**	**Min**	**Max**
lf	Overall	0.855	0.037	0.667	0.969
	Between		0.020	0.742	0.932
	Within		0.030	0.769	0.931
w	Overall	6.161	0.823	4.410	13.223
	Between		0.626	5.144	10.208
	Within		0.536	4.488	9.176
v	Overall	0.009	0.006	0.000	0.131
	Between		0.003	0.004	0.028
	Within		0.006	-0.007	0.123
u	Overall	0.051	0.031	0.001	0.144
	Between		0.014	0.019	0.105
	Within		0.027	-0.009	0.114
r	Overall	0.030	0.020	0.002	0.126
	Between		0.012	0.007	0.090
	Within		0.016	-0.013	0.078
jdr	Overall	0.107	0.042	0.028	0.528
	Between		0.015	0.067	0.152
	Within		0.039	0.018	0.483
$p1824$	Overall	0.146	0.017	0.099	0.214
	Between		0.011	0.119	0.190
	Within		0.013	0.100	0.182
$p5565$	Overall	0.193	0.027	0.101	0.298
	Between		0.025	0.123	0.280
	Within		0.011	0.153	0.251

A.2 Plots of data

Figure 2 - *Figure 9* show the Box-Whiskers plots of the data. Box-Whiskers plots presents the time-series pattern together with the distribution over municipalities. The box contains data between 25th to 75th percentiles, and the line in the box represents the median. Some extreme observations are dropped in the Figures. For the labor-force participation rate 3 observations that are less than 0.7 are dropped, 11 observations on vacancies that are greater than 0.4 are dropped, 9 observations on labor market programs that are greater than 0.1 are dropped, and 4 observations on the job destruction rate greater than 0.4 are dropped.

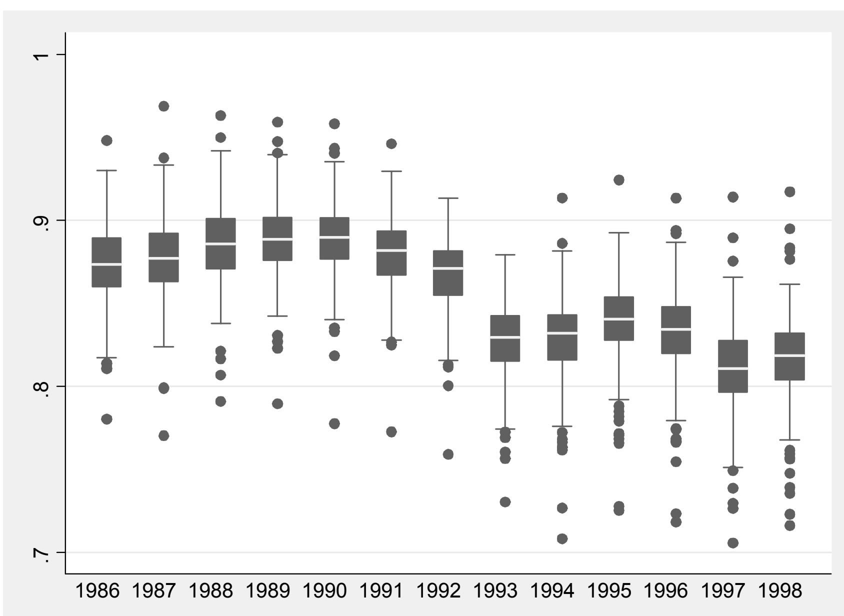

Figure 2: Labor force participation rate

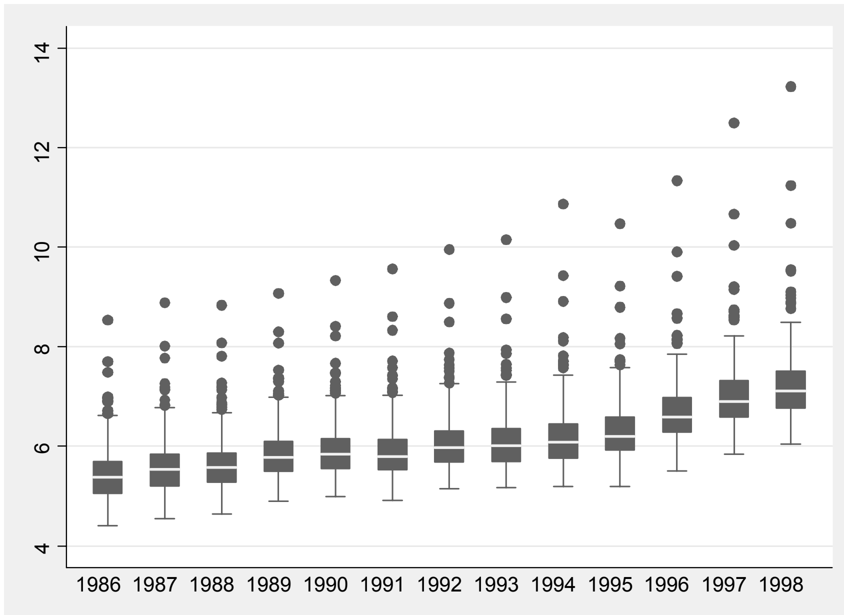

Figure 3: Real income for employed

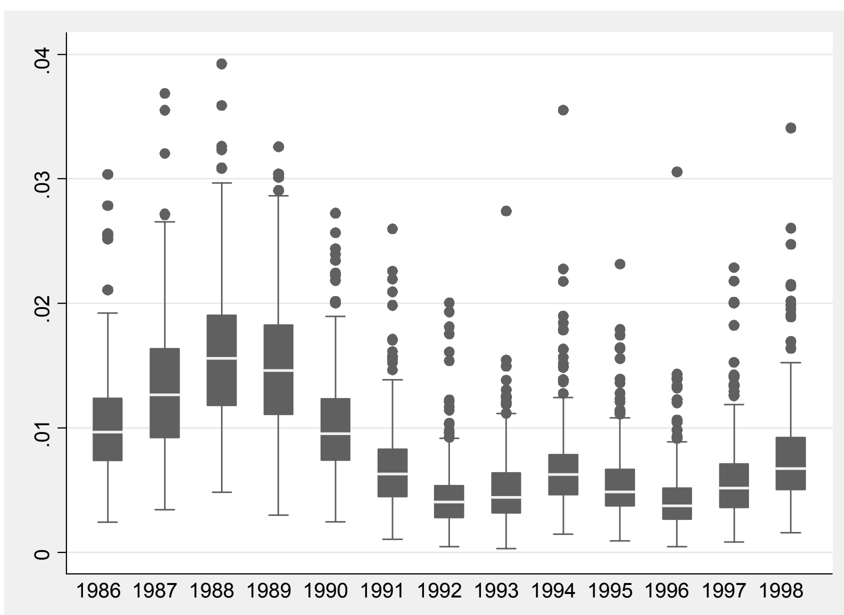

Figure 4: Vacancies divided by the working-age population

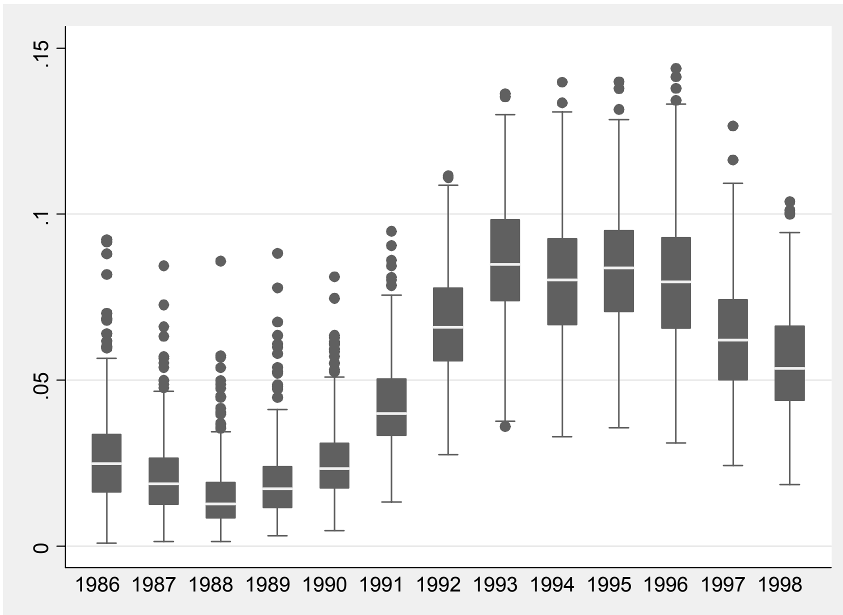

Figure 5: Unemployment divided by the working-age population

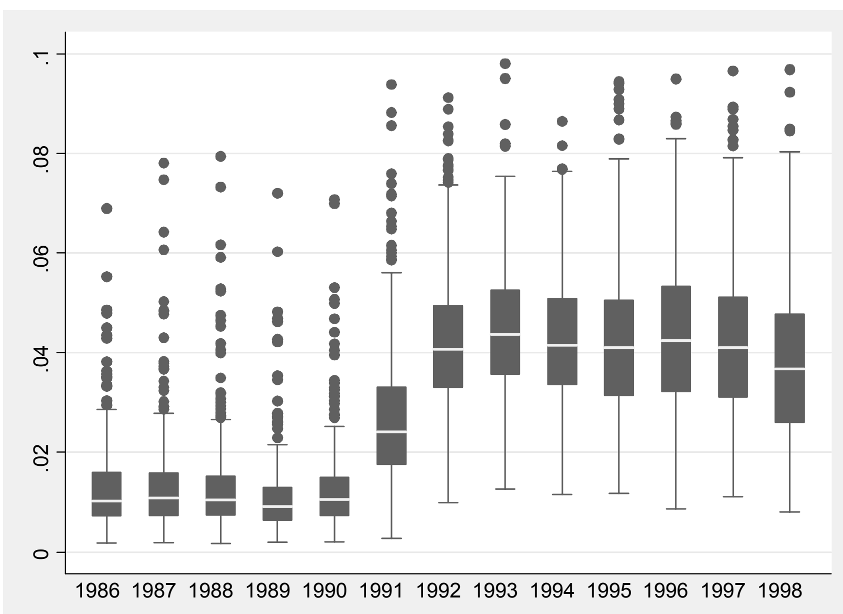

Figure 6: Participants in labor market programs divided by the working-age population

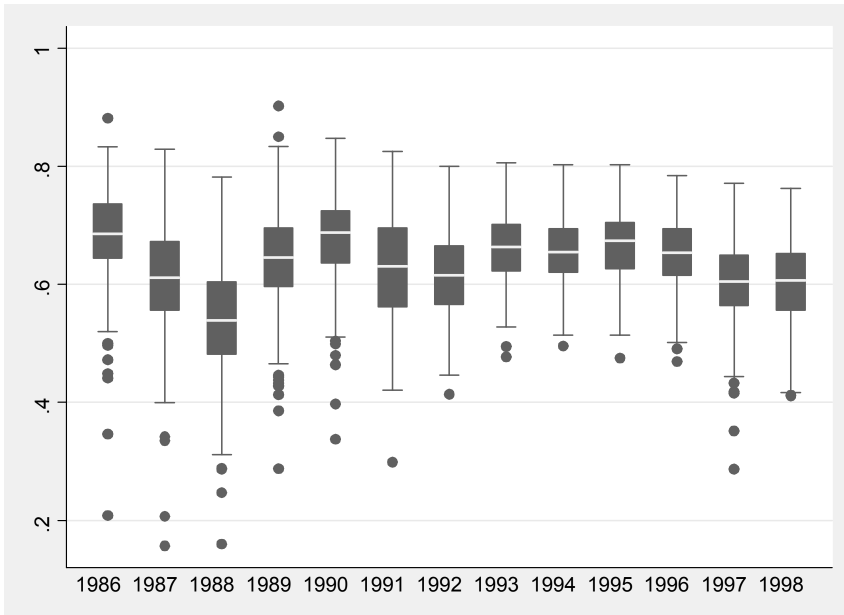

Figure 7: The accommodation ratio

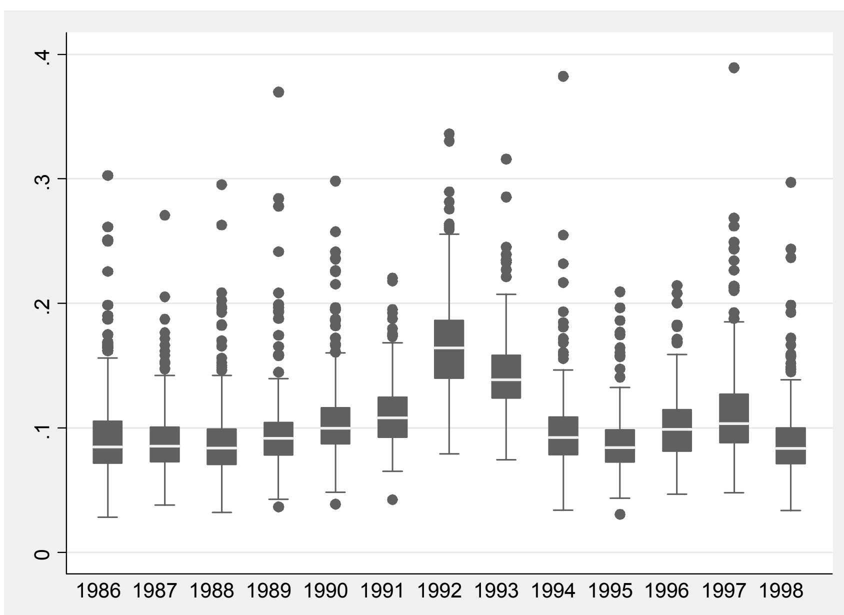

Figure 8: Population ages 18-24 divided by the working-age population

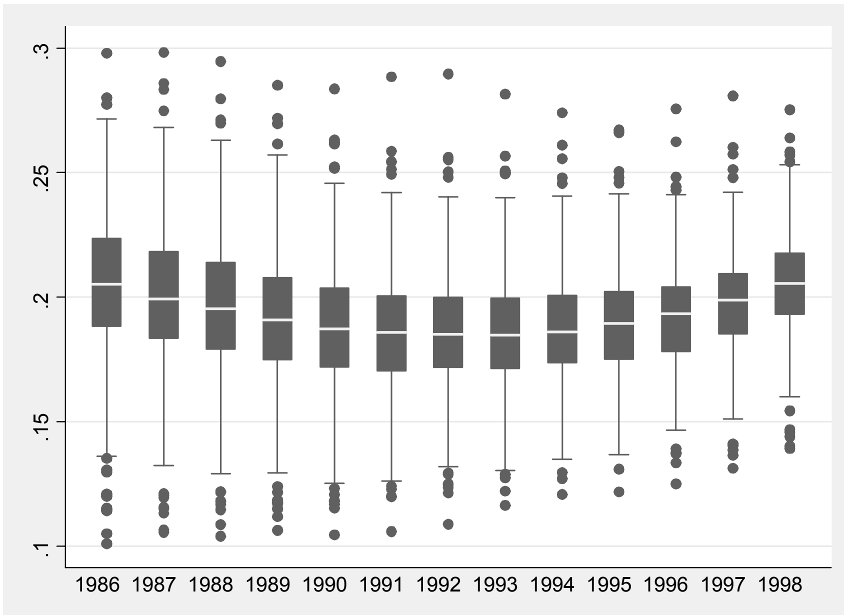

Figure 9: Population ages 55-65 divided by the working age population

B Detailed estimation results

Table 10: Estimation results, first step estimation

	Preliminary model			Reduced model		
Variable	**Coeff**	**p-val**	**SE**	**Coeff**	**p-val**	**SE**
lf_{t-1}	0.358	0.000	0.039	0.362	0.000	0.039
lf_{t-2}	0.046	0.044	0.023	0.035	0.114	0.022
w_t	0.008	0.038	0.004	0.004	0.071	0.002
w_{t-1}	-0.007	0.121	0.004			
w_{t-2}	-0.000	0.792	0.000			
v_t	0.081	0.583	0.147			
v_{t-1}	0.152	0.077	0.086	0.177	0.032	0.082
v_{t-2}	-0.030	0.514	0.046			
u_t	0.483	0.000	0.062	0.487	0.000	0.059
u_{t-1}	-0.524	0.000	0.058	-0.549	0.000	0.053
u_{t-2}	-0.160	0.000	0.043	-0.153	0.000	0.042
r_t	0.622	0.000	0.068	0.624	0.000	0.066
r_{t-1}	-0.218	0.000	0.060	-0.214	0.000	0.058
r_{t-2}	-0.048	0.277	0.044			
jdr_t	-0.127	0.000	0.022	-0.121	0.000	0.021
jdr_{t-1}	-0.012	0.103	0.007	-0.012	0.046	0.006
jdr_{t-2}	-0.000	0.986	0.006			
$p1824_{t-1}$	-0.403	0.000	0.056	-0.417	0.000	0.056
$p5565_{t-1}$	-0.158	0.001	0.049	-0.158	0.001	0.049
$Sargan$	674.4	0.000		743.0	0.000	
$AR(1)$	-10.0	0.000		-10.5	0.000	
$AR(2)$	2.3	0.024		2.4	0.018	

Table 11: Estimation results, time-dummies, second step estimation

	Preliminary model			**Reduced model**		
Variable	**Coeff**	**p-val**	**SE**	**Coeff**	**p-val**	**SE**
const	-0.0043	0.000	0.0012	-0.0044	0.000	0.0011
$t1990$	-0.0005	0.787	0.0019	-0.0019	0.256	0.0016
$t1991$	-0.0209	0.000	0.0023	-0.0208	0.000	0.0023
$t1992$	-0.0100	0.002	0.0032	-0.0086	0.007	0.0032
$t1993$	-0.0246	0.000	0.0033	-0.0247	0.000	0.0031
$t1994$	0.0279	0.000	0.0033	0.0286	0.000	0.0032
$t1995$	0.0082	0.001	0.0024	0.0071	0.002	0.0023
$t1996$	-0.0062	0.000	0.0017	-0.0055	0.000	0.0015
$t1997$	-0.0057	0.005	0.0020	-0.0071	0.000	0.0018
$t1998$	0.0123	0.000	0.0020	0.0110	0.000	0.0017
Sargan	259.6	0.392		268.6	0.343	
$AR(1)$	-7.5	0.000		-8.1	0.000	
$AR(2)$	1.5	0.142		1.6	0.122	

C Alternative estimations

This section presents results from alternative estimations of the model to examine if the estimation results are sensitive to estimation methods and assumptions made in the estimation. The following potential problems are considered:

1. The small sample performance of the estimator could be problematic if data are persistent. The model is therefore estimated with an alternative estimator that could perform better in small samples when data are persistent, which is often the case with macro-data.

2. All available information are not used in the estimation because only instrument dated $t-2$ to $t-4$ are used. The model is thus estimated with all available instruments to examine if the results are affected by the choice of instruments.

3. Several assumptions are made in the estimation. In the computation of standard errors it is assumed that the errors are independent between municipalities, although they are allowed to be heteroskedastic. Furthermore, the parameters are assumed to be constant for different time periods and for different municipalities. The assumptions of no spatial correlation in the errors and constant coefficients in the time and municipality dimension are relaxed in alternative estimations.

4. The estimated coefficient on labor market programs measures two effects; one direct positive effect of the value of participating in a program and one negative indirect negative effect of an increased number of searchers. An attempt to distinguish the two effects from each other is made by assigning values to an unobserved parameter.

Results with the SYS-estimator The GMM estimator for dynamic panel data models by Arellano and Bond (1991) that is used here, could have poor performance in small samples if the variables are persistent, because the instruments are weak if data is highly autoregressive, see Blundell, Bond, and Windmeijer (2000) and Blundell and Bond (1998). Macro-data are used in this study and they could be persistent. Blundell and Bond (1998) propose a linear GMM estimator (SYS) as an alternative to the Arellano and Bond (1991) first-differenced linear GMM estimator (DIF), when data are persistent.[24]

[24]The SYS-estimator uses lagged differences as instruments for the model in levels, in addition the instruments used by the DIF-estimator - lagged levels as instrument for the

AR(1) models, including time dummies, are estimated to examine the rate of persistence in data.[25] The point estimates could only indicate if variables are persistent because the models are rejected by the Sargan statistic. The estimation results indicate that wages is the only variable that may be persistent.[26]

The first column in *Table 12* in presents the estimation results for the preliminary model with the SYS-estimator. The corresponding results with the DIF-estimator is presented in *Table 3* in the main text. Except for the coefficients on unemployment, the estimation results do not change when the SYS-estimator is used. The estimated long run effect on open unemployment is -1.05 with the SYS-estimator compared to -0.28 with the DIF-estimator in the preliminary model. All other point estimates of the long run effect, including the effect of programs, are within the 90 % confidence bands for the reduced model estimated with the DIF-estimator (see *Table 5*).

Results with the full instrument matrix The number of lagged instruments that is used in the estimation is the smallest number that is accepted by the Sargan statistic, which are instruments dated *t-2* to *t-4*. So information contained in further lags of the instruments are not used in the estimation. To examine if the parameter estimates are sensitive to the number of instruments, the model is estimated with the total number of instruments available, that is, all available lags for each observation. The second column in *Table 12* presents the estimation results of the preliminary model with the full instrument matrix. In general, the parameter estimates are not sensitive to the number of lagged instruments in the estimation. The estimated long run effect of programs is smaller when the full instrument matrix is used, 0.35 compared to 0.66, but within the 90 % confidence band for the reduced model.

differences. Formally, the validity of the extra instrument used by the SYS estimator could be tested for using a difference Sargan test. But simulation results in Blundell, Bond, and Windmeijer (2000) indicate that the Sargan statistic for this test could be oversized when data are persistent. So it is difficult to reject the validity of the extra instruments used by the SYS estimator. Another reason could be that the instruments used by the DIF estimator are good enough.

[25]The AR(1) models are estimated with the DIF- and the SYS-estimator, with instruments up to lag *t-4* and all available instruments. In general, the models are rejected by the Sargan statistic. The difference between the estimated coefficients with the DIF- and the SYS-estimator and with different number of instruments is small.

[26]The labor force participation rate, unemployment, and labor market programs seem to be moderately autoregressive, with estimated autoregressive coefficients between 0.4 and 0.6. The autoregressive coefficients on vacancies and job destruction rate are probably small.

Table 12: Estimation results, preliminary model, SYS and DIF estimator

	SYS estimator			**DIF estimator**		
	instrument $t-2$ - $t-4$			all available instruments		
Variable	**Coeff**	**p-val**	**SE**	**Coeff**	**p-val**	**SE**
lf_{t-1}	0.591	0.000	0.031	0.458	0.000	0.035
lf_{t-2}	0.116	0.000	0.027	0.048	0.111	0.030
w_t	0.007	0.075	0.004	0.003	0.252	0.003
w_{t-1}	-0.007	0.107	0.004	-0.001	0.684	0.003
w_{t-2}	-0.000	0.645	0.000	-0.000	0.452	0.000
v_t	0.062	0.700	0.162	0.119	0.388	0.138
v_{t-1}	0.153	0.096	0.092	0.153	0.157	0.108
v_{t-2}	-0.121	0.052	0.062	-0.089	0.256	0.078
u_t	0.347	0.000	0.066	0.458	0.000	0.053
u_{t-1}	-0.571	0.000	0.063	-0.549	0.000	0.050
u_{t-2}	-0.079	0.074	0.044	-0.065	0.183	0.049
r_t	0.571	0.000	0.071	0.514	0.000	0.064
r_{t-1}	-0.373	0.000	0.068	-0.304	0.000	0.066
r_{t-2}	-0.053	0.251	0.046	-0.038	0.438	0.049
jdr_t	-0.108	0.000	0.021	-0.092	0.000	0.019
jdr_{t-1}	-0.012	0.136	0.008	-0.014	0.069	0.007
jdr_{t-2}	-0.002	0.776	0.007	-0.002	0.765	0.006
$p1824_{t-1}$	-0.357	0.000	0.052	-0.354	0.000	0.068
$p5565_{t-1}$	-0.123	0.000	0.034	-0.174	0.002	0.055
$Sargan$	261	1.000		269	1.000	
$AR(1)$	-8.8	0.000		-8.8	0.000	
$AR(2)$	1.2	0.214		1.9	0.062	

Results when the errors are correlated between municipalities In the calculation of the standard errors, it is assumed that the errors, $\varepsilon_{i,t}$, in equation (11) are independent between municipalities. The assumption could be problematic if the variables are measured at different local levels. Here, variables from local labor markets are included together with variables measured at the municipality level. Then, a so called Moulton bias could result in a downward bias of the estimated standard errors. The standard errors are also affected by spatial correlations between the municipalities. To get an indication of whether these two sources of bias are problematic, the model is estimated with the assumption that municipalities within the same local labor market[27] are allowed to have correlated errors, while errors between different local labor markets are uncorrelated.

To do this, the model is estimated with an ordinary IV-estimator.[28] The reduced model is estimated in differences, with lagged levels of the endogenous variables dated *t-2* to *t-5* as instruments.[29] *Table 13* presents the estimation results. The cluster option, which is used when local labor markets are allowed to be correlated, is only available with the robust option in Stata. The robust option calculates the standard errors by down-weighing the importance of outliers. The p-values are practically the same for normal and robust standard errors. The significance of the parameters do not change when the cluster option is used to calculate the p-values. So the conclusions do not change when errors are allowed to be correlated between municipalities in the same local labor market.

Table 13: Estimation results, IV-estimator

Variable	**Coeff**	**p-val ordinary**	**p-val robust**	**p-val cluster**
lf_{t-1}	0.282	0.000	0.001	0.001
lf_{t-2}	0.037	0.254	0.318	0.350
w_t	0.005	0.405	0.366	0.139
v_{t-1}	0.243	0.034	0.065	0.075
u_t	0.883	0.000	0.000	0.000
u_{t-1}	-0.413	0.036	0.032	0.011
u_{t-2}	-0.063	0.227	0.236	0.136
r_t	0.712	0.000	0.000	0.001
r_{t-1}	-0.192	0.201	0.197	0.107
jdr_t	-0.140	0.041	0.057	0.054
jdr_{t-1}	-0.020	0.021	0.023	0.020
$p1824_{t-1}$	-0.484	0.000	0.000	0.000
$p5565_{t-1}$	0.132	0.164	0.188	0.131

Results for different sample periods In the estimation it is assumed that the parameters are constant over time. The preliminary model is estimated on different sub-samples, to examine if the estimates change. The first

[27]The definition of local labor markets are based on commuting areas. There are 81 local labor markets.

[28]The estimation is carried out in Stata, using the ivreg command with the cluster option.

[29]The introduction of one more lagged level as instruments is necessary to obtain parameter estimates that are similar to the GMM-estimates. The estimation period is 1991-98.

and the last period were gradually deleted from the model. *Table 14* presents the estimation results from the second-step estimation when the sample is divided into two periods, 1989-94 and 1994-98.[30] The estimated coefficients, except on open unemployment, are about the same size as when the whole sample is used. The estimated sum of the coefficients on open unemployment differs between the sample periods. The estimated long run effect of open unemployment is positive when the model is estimated during 1994-98. The estimated long term effect of labor market programs is about the same in the different sample periods.

Table 14: Estimation results, different sample periods

	89-94		**94-98**	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**
lf_{t-1}	0.253	0.000	0.210	0.05
lf_{t-2}	0.009	0.845	0.038	0.292
w_t	0.006	0.372	0.012	0.094
w_{t-1}	0.008	0.373	-0.016	0.065
w_{t-2}	-0.000	0.195	0.000	0.610
v_t	0.149	0.492	0.304	0.304
v_{t-1}	0.185	0.129	0.378	0.163
v_{t-2}	-0.003	0.952	0.013	0.944
u_t	0.245	0.091	0.785	0.000
u_{t-1}	-0.571	0.000	-0.147	0.144
u_{t-2}	-0.128	0.097	-0.041	0.479
r_t	0.550	0.000	0.624	0.000
r_{t-1}	-0.070	0.549	-0.100	0.337
r_{t-2}	0.075	0.327	-0.027	0.602
jdr_t	-0.117	-0.000	-0.147	0.000
jdr_{t-1}	-0.016	0.114	-0.022	0.168
jdr_{t-2}	-0.007	0.402	-0.003	0.817
$p1824_{t-1}$	-0.439	0.000	-0.466	0.000
$p5565_{t-1}$	-0.203	0.019	-0.096	0.268
Sargan	190	0.005	156	0.005
$AR(1)$	-4.6	0.000	-3.4	0.001
$AR(2)$	1.5	0.125	0.9	0.370

[30] The Sargan statistic does not accept the models. When the estimation periods are extended to 1989-96 and 1992-98, the models are accepted by the Sargan statistic.

Results for different sizes of municipality populations In the estimation it is assumed that the parameters are the same in all municipalities. To examine if the estimation results are sensitive to the size of the population in each municipality, the preliminary model is estimated excluding municipalities with populations larger than 95 000, 50 000, and 20 000. About 95 %, 85 %, and 57 % of Sweden's population is covered. Municipalities with populations less than 7 500, 12 500 and 15 000 are also excluded, leaving samples covering about 90 %, 75 %, and 55 % of Sweden's population. *Table 15* presents the estimation results excluding larger municipalities and *Table 16* presents the estimation results where the smaller municipalities have been left out.

The point estimates, except for unemployment, do no change when municipalities with large populations are excluded. The point estimates of the long run effects of open unemployment vary between -0.12 to -0.19, which should be compared with -0.33 when the whole sample is used, indicating that labor-force participation in small municipalities could be less sensitive to municipality unemployment. The point estimated, except for vacancies, do no change when municipalities with small population are excluded. The point estimates of the long run effect of municipality vacancies vary between 0.5 and 1.3, which should be compared with 0.3 when the whole sample is used, indicating larger business cycle variation in the participation rate in large municipalities.

To summarize, the participation rate could be more pro-cyclical in large municipalities, because the effect of open unemployment is lower when large municipalities are excluded and the effect of vacancies is larger when small municipalities are excluded. The variables in the estimations are measured at the municipality level. Therefore, larger coefficients on vacancies in municipalities with larger population do not necessarily indicate that the effect is larger. It could be the case that it is, for example, vacancies at the local labor market, and not at the municipality level as in the estimation, that matters.

Table 15: Estimation results, exclusive of large municipalities

	pop $\leqslant$ 95 000		**pop $\leqslant$ 50 000**		**pop $\leqslant$ 20 000**	
	$n = 271$		$n = 241$		$n = 161$	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
lf_{t-1}	0.303	0.000	0.273	0.000	0.303	0.000
lf_{t-2}	0.022	0.365	0.027	0.323	0.080	0.041
w_t	0.008	0.103	0.012	0.040	-0.006	0.573
w_{t-1}	0.000	0.959	0.006	0.433	0.003	0.773
w_{t-2}	-0.001	0.056	0.001	0.766	-0.001	0.850
v_t	0.175	0.249	0.102	0.565	0.262	0.241
v_{t-1}	0.138	0.135	0.127	0.203	0.136	0.429
v_{t-2}	-0.034	0.433	-0.067	0.235	-0.017	0.855
u_t	0.518	0.000	0.529	0.000	0.632	0.000
u_{t-1}	-0.495	0.000	-0.455	0.000	-0.529	0.000
u_{t-2}	-0.151	0.001	-0.152	0.002	-0.179	0.014
r_t	0.625	0.000	0.647	0.000	0.601	0.000
r_{t-1}	-0.177	0.004	-0.120	0.086	-0.164	0.106
r_{t-2}	-0.025	0.581	-0.015	0.763	-0.009	0.903
jdr_t	-0.121	0.000	-0.108	0.000	-0.075	0.005
jdr_{t-1}	-0.012	0.107	-0.010	0.242	-0.013	0.323
jdr_{t-2}	0.000	0.997	0.001	0.835	0.001	0.902
$p1824_{t-1}$	-0.340	0.000	-0.291	0.000	-0.327	0.025
$p5565_{t-1}$	-0.180	0.000	-0.167	0.004	-0.091	0.307
Sargan	246.7	0.616	222.5	0.923	143.8	1.000
$AR(1)$	-7.5	0.000	-7.4	0.000	-5.7	0.000
$AR(2)$	1.5	0.128	1.4	0.156	0.8	0.441

Decomposition of the effect of labor market programs The estimated coefficients on the number of participants in programs measure two effects; one positive direct effect from the value of programs and one indirect negative effect from the number of effective searchers, $u + cr$. The parameter c in the theoretical model reflects differences in the probability of getting a job-offer between program participants and open unemployed. The two different effects could be separated by assigning values of c such that the number of effective searchers could be calculated. *Table 16* in Appendix B presents estimation results for the reduced model when the c-parameter is set to 0.5, 1, and 1.5 respectively. The number of effective searchers, $u + cr$, should measure the negative competition effect and the number of program participants, r, should measure the direct positive effect of programs. The

Table 16: Estimation results, exclusive of small municipalities

	pop ⩾7 500		**pop ⩾ 12 500**		**pop ⩾ 15 000**	
	$n = 245$		$n = 175$		$n = 144$	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
lf_{t-1}	0.390	0.000	0.442	0.000	0.448	0.000
lf_{t-2}	0.020	0.463	-0.008	0.814	0.008	0.841
w_t	0.007	0.067	0.004	0.141	0.002	0.401
w_{t-1}	-0.004	0.249	0.000	0.959	0.002	0.493
w_{t-2}	-0.000	0.400	-0.000	0.768	0.000	0.736
v_t	0.260	0.122	0.496	0.014	0.354	0.116
v_{t-1}	0.097	0.251	0.069	0.427	0.286	0.057
v_{t-2}	-0.058	0.217	0.007	0.903	0.050	0.721
u_t	0.482	0.000	0.418	0.000	0.417	0.000
u_{t-1}	-0.595	0.000	-0.461	0.000	-0.522	0.000
u_{t-2}	-0.124	0.011	-0.041	0.465	-0.050	0.483
r_t	0.896	0.000	0.647	0.000	0.520	0.000
r_{t-1}	-0.348	0.000	-0.212	0.008	-0.247	0.005
r_{t-2}	0.055	0.298	0.075	0.285	0.041	0.581
jdr_t	-0.118	0.000	-0.094	0.000	-0.067	0.000
jdr_{t-1}	-0.012	0.125	-0.017	0.056	-0.013	0.158
jdr_{t-2}	0.001	0.854	-0.005	0.433	-0.003	0.672
$p1824_{t-1}$	-0.462	0.000	-0.495	0.000	-0.532	0.000
$p5565_{t-1}$	-9,125	0.033	-0.160	0.077	-0.242	0.032
Sargan	227.1	0.887	151.5	1.000	122.2	1.000
$AR(1)$	-7.0	0.000	-6.0	0.000	-5.1	0.000
$AR(2)$	0.7	0.496	0.6	0.534	-0.3	0.751

direct and indirect effect are only separated empirically in the long run because the estimated immediate effect of the number of effective searchers is positive and not negative as expected. The estimated long run indirect effect is negative and direct effect is positive.

Table 17 in Appendix B presents the estimated immediate and long run direct and indirect effects of the number of participants in labor market programs for different values of c, where the coefficients on $u + cr$ are multiplied with the value of c. The total effect of programs is about the same size as in the estimation where c is unrestricted. The long run competition effect, calculated from the coefficient on $u + cr$, is increasing in c, as expected. The estimated long run direct effects of programs are also larger if programs are more effective, as expected.

Table 17: Estimation results, different assumptions about c

Variable	Coeff c=1	p-val	Coeff c=1.5	p-val	Coeff c=0.5	p-val
lf_{t-1}	0.356	0.000	0.357	0.000	0.366	0.000
lf_{t-2}	0.038	0.106	0.039	0.095	0.038	0.104
w_t	0.004	0.084	0.004	0.081	0.004	0.103
v_{t-1}	0.181	0.040	0.181	0.040	0.191	0.034
$u_t + cr_t$	0.482	0.000	0.446	0.000	0.475	0.000
$u_{t-1} + cr_{t-1}$	-0.534	0.000	-0.524	0.000	-0.513	0.000
$u_{t-2} + cr_{t-2}$	-0.140	0.001	-0.141	0.002	-0.113	0.005
r_t	0.156	0.084	-	-	0.417	0.000
r_{t-1}	0.330	0.000	0.578	0.000	-	-
r_{t-2}	0.120	0.034	0.188	0.011	-	-
jdr_t	-0.124	0.000	-0.125	0.000	-0.126	0.000
jdr_{t-1}	-0.012	0.041	-0.012	0.044	-0.012	0.048
$p1824_{t-1}$	-0.408	0.000	-0.410	0.000	-0.407	0.000
$p5565_{t-1}$	-0.153	0.002	-0.151	0.003	-0.162	0.001
Sargan	266.3	0.364	266.0	0.386	265.5	0.410
$AR(1)$	-8.0	0.000	-8.1	0.000	-8.2	0.000
$AR(2)$	1.4	0.154	1.5	0.133	1.6	0.115

Table 18: The direct and indirect effects of r

		$u + cr$	r	*total*
$c = 1$	immediate	0.482	0.156	0.638
	long run	-0.317	1.000	0.683
$c = 1.5$	immediate	0.669	-	0.669
	long run	-0.545	1.268	0.723
$c = 0.5$	immediate	0.238	0.417	0.655
	long run	-0.128	0.700	0.572
unrestricted	immediate			0.634
	long run			0.699

Essay II
Do labor market flows affect labor-force participation?*

1 Introduction

Few studies try to answer the question of whether labor market programs affect labor-force participation. This question is important in Sweden because the labor force is expected to decline due to the age distribution in the population. Today, there is a considerable focus on ways of attracting groups outside the labor force into it, for example recipients of social benefits, immigrants, and young people who have weak links with the labor market. Ways of retaining older workers in the labor force and attracting people who have left labor force for some reason have also been discussed. Labor market programs could be a factor in attracting new entrants and preventing participants from leaving the labor force.

Normally, studies of the effects of labor market programs use micro-data, and analyze the effects on the participants' future income or their probability of getting a job, see the overview by Calmfors, Forslund, and Hemström (2002). Studies using macro-data are more rare, and results for Sweden indicate that the displacement effect or direct crowding out could be relatively large, see for example Dahlberg and Forslund (1999). Results from reduced-form estimations indicate that programs reduce regular employment, see for example Calmfors and Skedinger (1995).

Here, the focus is on labor-force participation. It is important for the overall performance of the labor market that movements in and out of the labor force involve as little frictions as possible. In Sweden, labor-force participation is pro-cyclical, so people tend to leave labor force when it is difficult

*I am grateful to Anders Forslund and Kåre Johansen for comments and suggestion. I also thank seminar participants at IFAU and the Department of Economics at Uppsala University. Thanks to David Canter for correcting the language. The usual caveat applies.

to find a job and to enter labor force when it is easy to find a job. In other words, the discouraged worker effect is present. It is not a problem if participants move in and out of labor force when the business cycle changes. During the long period with extremely high unemployment rates in the early years of the 1990s, there was some fear that long-term unemployed might be so discouraged that they dropped out of the labor force permanently. Programs could be used to counteract the business-cycle variation in labor-force participation, and perhaps to prevent people from leaving labor force permanently.

Results in earlier studies indicate that labor market programs may have positive effects on labor-force participation in Sweden. This question has not been studied so much internationally, probably reflecting the large use of labor market programs in Sweden. Essay I in Johansson (2006) finds a relatively large and positive effect of labor market programs on labor-force participation. If the number of participants in programs is increased by 100 the number of participants in labor force is increased by 70 persons. The positive effect in Dahlberg and Forslund (1999) is obtained indirectly from their estimations of the displacement effects of labor market programs. These two studies use panel data for the Swedish municipalities. Positive effects are also found in studies using Swedish time-series data, (Wadensjö (1993) and Johansson and Markowski (1995)). These studies estimate the effect on labor-force participation from an increased stock of participants in labor market programs.

In this paper, I have constructed a new dataset, with monthly data for the Swedish municipalities from August 1991 to October 2002. The relatively large number of observations in the time-dimension makes it possible to estimate both the long run effect and the short run dynamics. Data for monthly employment and income at the municipality level are constructed in a new way. Existing data measure employment in November only, and the measure of income refers to the yearly income for those employed in November. Other papers study whether the number of participants in labor market programs increases the number of participants in labor force. This paper instead asks if an increased flow of persons from open unemployment into labor market programs increases labor-force participation.

The flow rate from open unemployment to labor market programs is a more interesting policy-variable, because it can be controlled more directly by policy makers, than the stock of program participants. Stocks can only be controlled indirectly, by changing the inflow or the average program duration. A typical policy question like "What happens to labor-force participation if we move people from open unemployment into program participation?" can be answered when the empirical model is formulated in flow terms. The policy experiment in the present paper is different from that in Essay I in Johansson (2006), who study the effect on labor-force participation of an increased number of participants in labor market programs. In this paper, the question is how labor-force participation is affected by increased flow rates between open unemployment and labor market programs.

2 Theoretical model

This section presents a theoretical model for labor force determination. The model is used to determine which variables should be included in the estimation and to determine their expected effects on labor-force participation. An individual will participate if the value of participating in labor force is larger than the value of non-participation. Participants in labor force could be employed, open unemployed or participate in a labor market program. Non-participants are for example students, part-time pensioner, or people that for other reasons chose to stay outside the labor force.

2.1 The model

The theoretical model is a search model with endogenously determined labor-force participation, based on Calmfors and Lang (1995), Holmlund and Lindén (1993), and Pissarides (1990). The same model is used in Essay I in Johansson (2006). In the model, the labor-force participation decision is based on a comparison between the value of participation and non-participation. Labor force participants can flow between three different labor market states. The factors determining the flows between the states are described, and the discounted values of being in each state are calculated. The parameter restrictions needed to ensure that regular employment is preferred to other states are presented before the effects on the labor-force participation rate are calculated. The theoretical model is slightly reformulated to correspond to the empirical measures available.

2.1.1 The states and flows in the labor market

Figure 1 describes states and flows in the labor market. The number of persons in each state is expressed in terms of the working-age population, and the population is assumed to be fixed. Labor force participants may be employed, e, openly unemployed, u, or participating in labor market programs, r, and $e+u+r=1$. The states and the flows for participants are the same as in Holmlund and Lindén (1993). Non-participants flow in and out from the

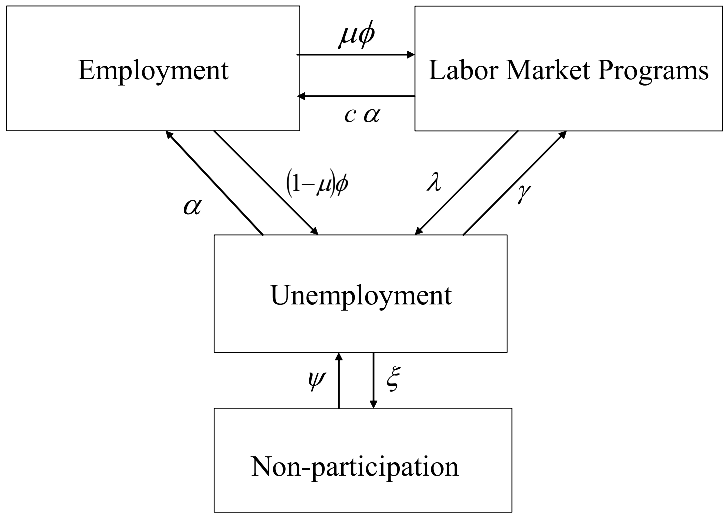

Figure 1: The states and flows in the labor market

labor force via open unemployment. The instantaneous flow rates in and out from non-participation depend on the realization of η and they are denoted ψ and ξ, respectively. It is assumed that all non-participants who want to participate in labor force have to be openly unemployed job seekers before moving to employment. This assumption is relaxed in the empirical analysis.

The job separation rate is denoted ϕ and represents exogenously given negative shocks to firms that result in reduced regular employment. A fraction $(1-\mu)$ of the number of persons that are separated from a job become unemployed, and a fraction μ is placed in a program. The probability of entering a program if openly unemployed is γ, and the probability of becoming unemployed after program participation is λ.

The firms are creating vacancies, and the openly unemployed and participants in labor market programs search for vacant jobs.[1] The number of matches depends on the number of vacancies and on the number of searchers, that is, the number of openly unemployed and participants in labor market programs. Increased labor market tightness, θ, (the number of vacancies divided by the number of searchers) increases the probability of getting a job

[1]There is no on-the-job search in the model.

offer, $\alpha(\theta)$.[2]

The probability of getting a job differs between the unemployed and the participants in labor market programs; the c parameter captures this difference. If c is greater than one, labor market programs have positive effects on the job-offer probability for the program participants compared to the openly unemployed. If c is less than one, program participants have smaller chances of getting a job offer than the openly unemployed. One reason could be that program participants search less than openly unemployed.

2.1.2 The labor-force participation decision

People in the working-age population choose to participate in the labor force if the value of participating is greater than the value of non-participation. More people will participate in the labor force if the value of participation is increased. When out of labor force, non-participants benefit from for example the value of leisure, the value of education or the value of other activities they are engaged in. Working hours are assumed to be fixed, so only full-time jobs are considered.[3]

The value of non-participation, $\delta\Lambda_{np,i}$, consists of two parts: (1) $f(z)$, that describes the impacts of variables outside the theoretical model, for example age, number of children and the supply of day-care services; (2) and η_i, a stochastic shock to preferences, which is uniformly distributed between $\eta_{\min}$ and $\eta_{\max}$. δ is the discount factor. The value of non-participation for an individual is

$$\delta\Lambda_{np,i} = f(z) + \eta_i. \tag{1}$$

η_i is the realization of the individual-specific shock. The labor force participant who is indifferent between labor-force participation and non-participation has $\delta\Lambda_{np,i} = \delta\Lambda_u$, where Λ_u is the value of being an unemployed job searcher and δ the discount factor. In the theoretical model, it is assumed that all non-participants who want to participate in labor force have to be openly

[2]To see this, assume that the number of hirings is determined by $h = h(s, v) = h(cr + u, v)$. The number of effective searchers, $s = cr + u$, and the number of vacancies, v, increase the matching function. Assume that all hirings come from the stock of searchers, $h = \alpha s = \alpha(cr + u)$. Then, the job offer arrival rate is $\alpha = h/s = h(s, v)/s$. If constant returns to scale are assumed for the h-function, we can express the job offer probability α as a function of labor market tightness, $\theta = v/s$. With constant returns to scale $\alpha = h(s, v)/s = h(1, v/s) = h(1, \theta) = \alpha(\theta)$, where $\theta = v/s$ is the labor market tightness. The job-offer probability α is increasing with labor market tightness θ.

[3]The reason for not allowing labor force participants to vary their labor supply is that data on the number of hours worked are not available in the dataset, so we cannot empirically distinguish between full-time and part-time workers.

unemployed job seekers before moving to employment.[4] The cut-off value, η_*, for the marginal participant is given by

$$\eta_* = \delta\Lambda_u - f(z). \tag{2}$$

The participation rate is the integral of the density function for η up to the cutoff value, which takes the following expression when η_i is uniformly distributed:

$$\int_{-\infty}^{\eta_*} \frac{1}{\eta_{\max} - \eta_{\min}} d\eta = \frac{\eta_* - \eta_{\min}}{\eta_{\max} - \eta_{\min}} \tag{3}$$

The participation rate is the proportion of the working age population that has a value of η_i up to η_*. Substitute the expression for η_* in equation (1) in equation (3) to express the participation rate as a function of the variables in the model:

$$\frac{lf}{pop} = \frac{\delta\Lambda_u - f(z) - \eta_{\min}}{\eta_{\max} - \eta_{\min}}. \tag{4}$$

The participation rate depends positively on the discounted value of being a job seeker, $\delta\Lambda_u$. The effect of $f(z)$ on the participation rate is assumed to be negative[5]. To summarize, the model predicts that the participation rate increases in the same variables that increase the value of being an unemployed job seeker, Λ_u.

2.1.3 The value of the states for labor force participants

The discounted value of the different states (employment, $\delta\Lambda_e$, open unemployment, $\delta\Lambda_u$, and program participation, $\delta\Lambda_r$) is computed as the discounted income in each state - accounting for the probability of changing state and the income in the new state.

$$\delta\Lambda_e = \left[w + (1-\mu)\,\phi\,(\Lambda_u - \Lambda_e) + \mu\phi\,(\Lambda_r - \Lambda_e)\right] \tag{5}$$

$$\delta\Lambda_r = \left[\rho_r w + c\alpha\,(\Lambda_e - \Lambda_r) + \lambda\,(\Lambda_u - \Lambda_r)\right] \tag{6}$$

[4] This assumption is relaxed in the empirical analysis.

[5] If Λ_u and $f(z)$ contain the same variables, it is assumed that the positive effect of variables in Λ_u is small in relation to the negative effect of $f(z)$. In a model with an endogenously determined value of leisure, the value of leisure depends on parameters in the utility function. The value of leisure will be an increase in wealth; a variable that could be affected by the same variables as Λ_u. It is assumed that possible effects of wealth are small.

$$\delta\Lambda_u = \left[\rho_u w + \alpha\left(\Lambda_e - \Lambda_u\right) + \gamma\left(\Lambda_r - \Lambda_u\right)\right] \tag{7}$$

Employed workers earn w and the conditional probabilities of open unemployment or participation in a program are $(1-\mu)\,\phi$ and $\mu\phi$. Participants in labor market programs earn $\rho_r w$ and they become employed or openly unemployed with probabilities $c\alpha$ and λ. Openly unemployed earn $\rho_u w$, and they become employed or placed in a labor market program with probabilities α and γ. Equations (5)-(7) are used to calculate the value of the states for labor force participants.[6]

An unemployed person accept job offers if the value of employment is greater than or equal to the value of being unemployed, $\Lambda_e \geqslant \Lambda_u$. The condition is:

$$\mu\phi\left(\rho_r - \rho_u\right) \leqslant \gamma\left(1-\rho_r\right) + \left(\delta + \lambda + c\alpha\right)\left(1-\rho_u\right) \tag{8}$$

This condition is likely to be satisfied for normal parameter values, where $\rho_u \leqslant \rho_r \leqslant 1$, because $\mu\phi$, the flow rate from employment to labor market programs, is small compared to the other rates in the expression. Furthermore, the difference $\left(\rho_r - \rho_u\right)$ is presumably smaller than $\left(1-\rho_r\right)$ and $\left(1-\rho_u\right)$. If the levels of the replacement rates are restricted, so that the replacement rate is the same for program participants and openly unemployed, $\rho_r = \rho_u = \rho$, the condition in (8) is satisfied if $\rho \leqslant 1$.

Program participants accept a job offer if the value of employment is greater than the value of participating in a program, $\Lambda_e \geqslant \Lambda_r$. The condition is:

$$\phi\left(1-\mu\right)\left(\rho_r - \rho_u\right) \leqslant \left(\alpha + \gamma + \delta\right)\left(1-\rho_r\right) + \lambda\left(1-\rho_u\right) \tag{9}$$

This condition is likely to be satisfied for realistic values of the replacement rates, $\rho_u \leqslant \rho_r \leqslant 1$, because the flow rate from employment to open

[6] The expression for the values of the states are the following:

$$\begin{aligned}
\Lambda_e &= w\left(\delta\Delta\right)^{-1}\left\{\left[\phi\left(\left(1-\mu\right)\left(\delta + c\alpha\right) + \lambda\right)\right]\rho_u + \left[\phi\left(\mu\left(\alpha+\delta\right)+\gamma\right)\right]\rho_r + \right.\\
&\quad \left. +\delta\left[\delta + \alpha\left(c+1\right) + \gamma + \lambda\right] + \alpha\left[\lambda + c\left(\gamma+\alpha\right)\right]\right\}\\
\Lambda_r &= w\left(\delta\Delta\right)^{-1}\left\{[\delta(\gamma+\delta+\alpha+\phi) + \phi(\gamma+\mu\alpha)]\rho_r + \right.\\
&\quad \left. +[\phi(\lambda + c\alpha(1-\mu)) + \delta\lambda]\rho_u + \alpha[c(\alpha+\delta+\gamma)+\lambda]\right\}\\
\Lambda_u &= w\left(\delta\Delta\right)^{-1}\left\{\left[\left(\delta+\phi+\lambda+c\alpha\right)\delta + \phi(c(1-\mu)\alpha+\lambda)\right]\rho_u + \right.\\
&\quad \left. +[\phi(\gamma+\mu\alpha)+\delta\gamma]\rho_r + [\delta + c(\gamma+\alpha)+\lambda]\alpha\right\}\\
\text{where } \Delta &= \left(\delta + c\alpha + \lambda\right)\left(\delta+\phi+\alpha\right) + \gamma\left(\delta+\phi+c\alpha\right) + \left(1-c\right)\alpha\mu\phi.
\end{aligned}$$

unemployment, $\phi(1-\mu)$, has to be smaller than the sum of the flow from open unemployment to employment, α, the flows rates between unemployment and program participation, γ and λ, and the discount factor, δ. The condition could be violated if the difference between the replacement rates is large enough. For the special case when $\rho_r = \rho_u = \rho$, the condition in (9) is satisfied if $\rho \leqslant 1$.If $\rho_u < \rho_r = 1$, the condition in (9) is satisfied if $\phi(1-\mu) \leqslant \lambda$, so the flow from employment into unemployment must be smaller than or equal to the flow from programs into unemployment.

An unemployed person accepts a place in a program if the value of participation in a program is greater than the value of being openly unemployed, $\Lambda_r \geqslant \Lambda_u$. The condition is:

$$(\phi+\delta)(\rho_r-\rho_u) \geqslant \alpha((1-\rho_r)-c(1-\rho_u)) \tag{10}$$

When $\rho_r = \rho_u < 1$, the condition in (10) is satisfied if $c \geqslant 1$. The parameter c captures all differences in the probability of getting a job-offer between program participants and openly unemployed. The job-offer probability for program participants has to be at least as large as for openly unemployed, because the replacement rates, and therefore income, are the same. On the other hand, if $c < 1$, program participants have to be compensated for the reduced probability of getting a job, so $\rho_r > \rho_u$. Involuntary flows from unemployment to programs could be observed, because unemployed people could be forced to participate in programs in order to retain their benefits. In such cases, the self-selection constraint in (10) is not fulfilled. Note that if programs are used to qualify the unemployed for new periods of unemployment benefits, it would increase the value of Λ_r, and relax the constraint in (10). This effect of programs is not included in the model. Taken together, the self-selection constraints imply that $\Lambda_e \geqslant \Lambda_r \geqslant \Lambda_u$. Restrictions on the policy parameters, $\lambda, \gamma, \mu, \rho_r$, and ρ_u are needed to satisfy the selection constraints.

2.1.4 Reformulation of the model to correspond to empirical measures

The labor-force participation rate depends positively on the value of being a job seeker, Λ_u, see equation (4), implying that new participants enter open unemployment. Empirically, we observe flows between non-participation and all three states of labor-force participation. Unfortunately, data do not cover all job seekers, only unemployed persons who are registered at an employment office are covered.

The theoretical model could be slightly reformulated to correspond to the empirical measures. Let the cutoff value, in (2), be $\eta_* = \delta\Lambda_e - f(z)$, then the participant who is indifferent between participation and non-participation has $\delta\Lambda_{np} = \delta\Lambda_e$, - in other words the value of non-participation is equal to the value of employment. The new entrants could then enter regular employment. For the purposes of of the model in this paper, it does not matter which state non-participants enter, because the values of the different states react in the same direction to the same shock, see Table *1*.

2.2 The effects on the labor-force participation rate

The way in which the values of the states in the labor market and the participation rate are affected by changes in the model's parameter is displayed in Table 1. Λ_e, Λ_r, Λ_e are the discounted values of the expected income in the different states for labor force participants, employment, labor market programs, and open unemployment.

Table 1: Effects on the labor-force participation rate

Increase in	**Effect on**				
	Λ_u	Λ_r	Λ_e	participation rate	
w, wage	+	+	+	+	
ρ_r, ρ_u, replacement rates	+	+	+	+	
γ, rate u to r	+	+	+	+	if $\Lambda_r - \Lambda_u \geqslant 0$
λ, rate r to u	-	-	-	-	if $\Lambda_r - \Lambda_u \geqslant 0$
μ, share from e to r	+	+	+	+	if $\Lambda_r - \Lambda_u \geqslant 0$
c, relative eff of program	+	+	+	+	if $\Lambda_e - \Lambda_r \geqslant 0$
ϕ, rate from e to u and r	-	-	-	-	if $\rho_r, \rho_u \leqslant 1$
$\alpha(\theta)$, rate from u and r to e	+	+	+	+	

An increase in wages, w, increases the value of participation and thus increases labor-force participation. ρ_r and ρ_u are the replacement rates (income as a fraction of earnings) during program participation or unemployment. Higher replacement rates increase the value of labor-force participation in the same way as higher wages.

Increased inflows into programs, γ, and increased shares of laid-off workers who enter directly into labor market program, μ, have positive effects on labor-force participation if the value of participating in a program is larger than being openly unemployed, that is, if $\Lambda_r - \Lambda_u \geqslant 0$. And increased outflow rates from programs into unemployment, λ, have negative effects if $\Lambda_r - \Lambda_u \geqslant 0$.

The self-selection constraint, $\Lambda_r - \Lambda_u \geqslant 0$, in (10) is fulfilled if the income for program participants is larger than for openly unemployed. This has been the case for some programs. Often, participants in job-creation programs are paid more than the unemployment benefit, while participants in training programs receive the unemployment benefit. If the income for unemployed and program participants is the same, labor-force participation is increased if $c \geqslant 1$, so that program participants have a greater probability of getting a job then open unemployed persons.[7] The parameter c could decrease during participation in some programs. It is, for example, natural to terminate a training program before searching for a new job. Naturally, the time left for job search is less when participating in full-time programs. If $c < 1$, the program's participants have to be compensated by a larger income compared with the openly unemployed.[8] Furthermore, if programs are used to qualify for new periods of unemployment benefits, the value of programs relative to open unemployment increases, and the restriction, $\Lambda_r - \Lambda_u \geqslant 0$, is eased. The selection constraint $\Lambda_r - \Lambda_u \geqslant 0$ has to be fulfilled in order to determine the sign of the effect on labor-force participation from increased probabilities of moving between open unemployment and labor market programs, γ and λ. If laid-off workers have an increased probability of participating in a program instead of becoming openly unemployed - an increase in the parameter μ in the model - the labor-force participation rate will increase if $\Lambda_r - \Lambda_u \geqslant 0$.

In the model, an increase in the relative effectiveness of programs, c, directly increases the probability of moving from programs to employment. If c increases, the participation rate is expected to increase, if $\Lambda_e - \Lambda_r \geqslant 0$ because the probability of finding a job and receiving a higher income has increased. The condition, $\Lambda_e - \Lambda_r \geqslant 0$, is likely to be fulfilled for normal parameter values, see the discussion of equation (9).

Labor market tightness, $\theta = (v/(u + cr))$, the number of vacancies divided by the number of effective job-searchers, affects the flow rates from unemployment and labor market programs into regular employment. An increased number of vacancies, v, increases the probability of finding a job and is expected to have a positive effect on labor-force participation. Increased numbers of openly unemployed persons, u, or program participants, r, increase the number of persons searching for jobs and, for a given number of vacancies and a given relative effectiveness of programs, c, it is now more difficult to find a job. The job-offer probability, $\alpha(\theta)$, depends on labor market tightness, (θ), which gives rise to the discouraged-worker effect in the model because labor market tightness is pro-cyclical.

An increased job separation rate, which is a negative employment shock,

[7] Remember that c captures all differences in job-offer probabilities between openly unemployed, and participants in labor market programs.

[8] Of course, the compensation could be a combination of higher expected probability of getting a job offer and an anticipated higher wage after the program.

ϕ, increases the probability of being openly unemployed. This is expected to have a negative effect on the labor-force participation rate because the probability of recieving a reduced income has increased since unemployment benefits are lower than wages.

To summarize, we expect the following variables to affect labor-force participation rate: the wage, w, the replacement rates, ρ_r and ρ_u, the flow rates from open unemployment to programs, γ, and from programs to open unemployment, λ, the share of negative employment shocks to program, μ, the relative effectiveness of programs, c, the flow rates from employment to open unemployment, $(1-\mu)\,\phi$, and from employment to program, $\mu\phi$, and the flow rate from open unemployment to employment, $\alpha\,(\theta)$.

3 Data

The data are a panel of monthly observations between August 1991 and October 2002 for Swedish municipalities. The number of observations is $284 \times 135 = 38\ 340$. Data on income and employment are new and compiled on a monthly basis. The alternative is the existing data in Rams[9]. Unfortunately, Rams measures employment in November only, and income for those employed in November is their yearly income and not their income in November.

The Händel database from the National Labour Board, available at IFAU, contains information on all individuals who are registered at an employment office as job searchers. Händel is used to calculate the gross flows between unemployment and labor market programs, and to compute the stock of the number of persons who are openly unemployed or participating in labor market programs.

3.1 The new data

Data on individual employment and income are calculated from a register of the tax authorities' statement of income[10]. Data on income from different employers are available, for every individual. Income and the first and the last month the income is paid out are recorded, for every employer. Monthly data on income are calculated on the assumption that the income is evenly distributed on a monthly basis. For each individual, the total income is

[9] The employment register at Statistics Sweden.

[10] The firms have to send a statement of income for each employee to the tax authorities. The statement contains the income and the initial and final month for the payment period, together with the identification number for the plant, the Cfar-number.

calculated as the sum of the monthly distributed income from all income statements. To classify the individual as employed or not, a lower limit for the income is used. If the income is lower than the cutoff value, the individual is classified as non-employed.[11] The cut-off value that is used here is 75 % of the wage for a male cleaner employed in the municipality sector.[12] Self-employed persons with an income of more than SEK 100 per month are defined as employed. Statements of income for self-employed persons do not contain information on the starting and ending month, so the income for self-employed persons is distributed evenly over the whole year.

The cutoff here is relatively high, but still at the bottom of the income distribution range. The same cutoff value is used for employees of all ages. It turns out that using the same income cutoff works surprisingly well. I have calculated the number of employed persons in different age groups using the same implicit income cutoff as in Rams 1998 for all persons employed.[13] The correspondence between the numbers of persons in different age groups is very close to the number of persons employed according to Rams. This is surprising because a sophisticated model is used in Rams to determine the income cutoff value. The correspondence with Rams is less for older people. For example, when calculating employment for men and women separately, for the 55-59 and 60-64 age groups, the differences were relatively large compared with Rams. But if, instead, employment for men and women were calculated for the 55-64 age group, the number of employed persons comes very close to Rams.

There is seasonal variation in the employment data, with higher employment, for example, during the summer months. Both employment and income increase dramatically in January each year. The increase in January is due to a cohort effect, arising from the fact that age is measured yearly and the other variables are measured monthly. The cohort effect is largest for the 55-64 age group, and the seasonal variation is more pronounced for persons in the 18-64 age range.

The calculations of monthly employment and income are based on the assumption that the starting and ending months in the statement of income are correct and that income should be equally distributed across the months.

[11] Non-employed persons could be openly unemployed, participating in a labor market program, or out of labor force.

[12] The cut-off in 2002 is SEK 11 477.

[13] The implicit cutoff value used in calculating November employment by Statistic Sweden is SEK 2 275 in November 1998. The employment definition used by Statistics Sweden should correspond to the labor force survey definition, i.e. those who have worked one hour every week are employed. The cutoff value that is used here for 1998 is SEK 6 600 per month.

One disadvantage is that the computation of employment has to rely on a cutoff-value for income. The same person could be classified as both employed and unemployed or in a program, if the income for this person is above the cutoff value and if the individual is registered in Händel during the same period.

3.2 Variables in the estimation

The theoretical model in Section 2 suggests that the following variables should affect labor-force participation rate: the wage, w, the flow rates between the different states, γ, λ, ϕ, and $\alpha(\theta)$, the share of the job separation rate that goes to program, μ, the relative effectiveness of programs, c, and the replacement rates, ρ_r ρ_u. This section presents the empirical definition of the variables. The expected effects of the empirical variables are indicated in Table 2.

The labor force is calculated as the sum of employed, openly unemployed and participants in labor market programs. Employment is the sum of the number of persons classified as employed in each municipality. Non-participants are the working-age population in the age range 18-65, excluding people in the labor force. With this definition, all participants in labor market programs are in the labor force. The population in each municipality is measured in December. The labor-force participation rate, lf, is labor force divided by population in December of the previous year.

The wage is measured by the monthly labor income for those employed, inc. Increased income is expected to increase labor-force participation. The flow rates between open unemployment and labor market programs, $[u \rightarrow r]$ and $[r \rightarrow u]$, are measured by the gross flow between the states, divided by the lagged number of persons in the outflow stock. Inflow into programs is expected to increase participation and outflow from programs is expected to reduce labor-force participation.

In the theoretical model, the flow rate from open unemployment and labor market programs to employment α, should be a function of labor market tightness, $\theta = v/\left(u + cr\right)$, the number of vacant jobs divided by the number of effective job-seekers, the stock of openly unemployed persons, u, and the stock of program participants, r, multiplied by the effectiveness parameter c.[14] It is assumed that there is no difference between unemployed persons and program participants as job-searchers, so $c = 1$ in the computation.

[14] The formulation of the labor market tightness variable implicitly assumes that there is constant return to scale in the matching function. Results in Forslund and Johansson (2006) indicate that the constant returns to scale assumption could not be rejected in log-linear matching functions.

Increased labor market tightness, *teta*, is expected to increase labor-force participation. It is possible to compute the number of persons who leave Händel for employment, which could be an alternative measure. Unemployment in the theoretical model refers to unemployed people who are looking for jobs. Unemployment in Händel is people who have registered at an employment office. In reality, we see flows from outside labor force to employment, and this flow will not be captured if Händel data are used to measure the inflow to employment. Labor market tightness is used instead. The flow from employment, job separations, is measured by the job destruction rate, *jdr*. The number of destroyed jobs is defined as the absolute sum of negative employment changes in each employment unit.[15] The job destruction rate is calculated by dividing job destruction with lagged employment at each employment unit. The job destruction rate is expected to have a negative effect on the labor-force participation rate.

Data on replacement rates, which should affect labor-force participation, are not available at the municipality level. The stocks are measured at the end of each month and the flow is measured during the month. Table 2 summarizes the discussion of the empirical variables and their expected effect on the labor-force participation rate. Summary statistics and plots of data are found in Appendix A.

Table 2: The empirical variables and the expected effect on the labor-force participation rate

Variable	**Definition**	**Effect**
lf	number of people in labor force$_t$/pop1865$_{t-1}$	
inc	w, real monthly income for employed$_t$	+
$[u \rightarrow r]$	γ, flow u to r_t/stock u_{t-1}	+
$[r \rightarrow u]$	λ, flow r to u_t/stock r_t	-
$teta$	θ, tightness $v/(u+r)$	+
jdr	ϕ, job destruction rate	-

3.3 The policy experiment

This paper focuses on the effect of labor market programs on labor-force participation, and the in policy variable is the flow from open unemployment to labor market programs. Other possible measures of policies are the outflow

[15]Self-employed persons are excluded from the calculation. If a person has several statements of income, the Cfar-number for the one with the largest income is used.

from programs to open unemployment, the number of participants in programs, and replacement rates. These measures are not considered here, either because they cannot be directly controlled by the local labor market offices (which are responsible for the implementation of the policy) or there are no good empirical measures for them. The flow from open unemployment into labor market programs can be controlled directly, because the labor market office decide which unemployed that should get an offer to participate in a labor market program. The outflow from programs into open unemployment is related to the duration of the programs and could only be controlled indirectly. Furthermore, voluntary quits and dropouts from programs occur. The disadvantage of using the number of program participants as policy variables is that the stock depends on the flows between programs and the other states.

The stock of participants in programs shows up indirectly in the estimation, as the denominator in the labor market tightness variable, *teta*, reflecting an indirect negative effect of labor market programs in the model. If, for a given number of vacancies, the number of job-searchers increases, the competition for vacant jobs increases, resulting in a negative effect on labor force. Only the results of tightness will be discussed, and not the separate effect of vacancies and the number of job-searchers.

In the policy experiment, where the flow from unemployment into programs is permanently increased, it is possible that the number of unemployed persons goes to zero, and the number of participants in labor market programs infinitely large. Therefore, the results of this experiment should be interpreted carefully, remembering that it only measures effects over the business cycle horizon. To carry out an experiment with results that are valid in the long run, steady state or stock flow equilibrium have to be imposed. Necessary data to impose such restrictions are not available.

4 Empirical results

A dynamic model is estimated. Both lagged effects of the explanatory variables and gradual adjustment in the dependent variables are allowed. A relatively large number of lags are probably needed when monthly data are used. All explanatory variables are assumed to be predetermined with respect to labor-force participation. That is, they could be correlated with contemporaneous and future values of the error term in the estimated equation, but not with lagged values of labor-force participation. This means that forecasts made today of future explanatory variables are not allowed to affect labor-force participation today.[16]. No attempt will be made to estimate the contemporaneous effects. Models are estimated for participants in the 18-64 age range, with separate models for men and women.

4.1 Estimation method

Panel data models are used, primarily because the number of observations is then sufficiently large to estimate both the short run adjustment and the long run effects. It is possible to estimate separate time-series models for each municipality, avoiding the panel-data restriction of equal coefficients for the variables. But, on the other hand, the number of observations in the individual time series model is too small to estimate the short run dynamics with sufficient accuracy.[17]

The commonly used estimators for panel data models, for example the within-group estimator, are not suitable when the variables are predetermined, because strict exogeneity is required, if an individual specific term is included.[18] If T becomes large, the within-group estimator is consistent for models with predetermined variables. Here it is assumed that the number of observations in the time dimensions is sufficiently large for consistent estimation. This assumption is probably valid because the average of the estimated long run effects is the same if separate models for each municipality are estimated, as when the within group estimator is used.

4.2 Estimation results

Panel data models with lags in all variables are estimated for the labor-force participation rate. Models are estimated for participants in the 18-64 age range, with separate models for men and women. The estimated results of models for participants in the 18-24, 25-39, 40-54, 55-64 and 25-54 age groups are reported in Appendix C. The estimated models have the error-correction form:

[16]The assumption is probably not problematical because it will normally take more than a month for nonparticipants to adjust their behavior to changes in expectations of the future labor market situation, for example.

[17]The dataset contains 135 monthly observations for 284 municipalities.

[18]Predetermined variables have to be transformed into first differences or orthogonal deviation. Lagged levels of the variables are valid instruments for the transformed variables.

$$
\begin{aligned}
\Delta lf_{age,i,t} \quad = \quad & \sum_{j=1}^{j=p-1} a_j \Delta lf_{age,i,t-j} + \sum_{j=1}^{j=p-1} b_{1j} \Delta inc_{age,i,t-j} + \\
& \sum_{j=1}^{j=p-1} b_{2j} \Delta \left[u \rightarrow r\right]_{age,i,t-j} + \sum_{j=1}^{j=p-1} b_{3j} \Delta \left[r \rightarrow u\right]_{age,i,t-j} lf \\
& + \sum_{j=1}^{j=p-1} b_{4j} \Delta teta_{age,i,t-j} + \sum_{j=1}^{j=p-1} b_{5j} \Delta jdr_{i,t-j} \\
& + a(1) lf_{age,i,t-1} + b_1(1) inc_{age,i,t-1} + b_2(1) \left[u \rightarrow r\right]_{age,i,t-1} \\
& + b_3(1) \left[r \rightarrow u\right]_{age,i,t-1} + b_4(1) teta_{age,i,t-1} + b_5(1) jdr_{i,t-1} \\
& + k_i + k_t + k_{seas,i} + \varepsilon_{i,t}
\end{aligned}
$$

The coefficients on the lagged level of the variables are the sum of the coefficients for each lag polynomial in the model, in levels, and the coefficients for the difference terms are functions of the original coefficients in the model, in levels. Prior to estimating, all variables are seasonally adjusted using centered seasonal dummies. Separate seasonal models are estimated for each municipality. Common time-specific effects are removed by estimating panel data models with time dummies for each seasonally adjusted variable. Panel data models are then estimated using the within-group estimator. There are 284 municipalities in the dataset, and together with the 135 months between August 1991 and October 2002, the total number of observations is 38 340.

All variables are measured at the municipality level, with the exception of labor market tightness, $teta$, and the job destruction rate, jdr. Labor market tightness, $teta$, is related to the probability of finding a job, and the job destruction rate, jdr, to the probability of losing a job. These variables are measured at the local labor market level[19], because local labor markets reflect where most inhabitants in each municipality work. Labor market programs are typically only offered in the home municipality, so the flows between open unemployment and labor market programs, $[u \rightarrow r]$, and $[r \rightarrow u]$ are measured at the municipality level. Income, inc, is measured as the average income for the employed person in each municipality, and it reflects the actual income for different jobs in the municipalities.

All models, including those for the separate age groups in Appendix C, have the same lag length in the estimations, $p = 7$. This is the number of lags where the tests, on average for the age groups, show less significant signs of

[19]The definition of local labor markets is based on commuting patterns. The number of local labor markets is 100 and the number of municipalities is 284.

correlation in the residuals. The estimated long run effects are not sensitive to how many lags are included in the models.

Table 3: The estimated long run effect for the 18-64 age group

Variable	**Effect**	**p-val**	**p-val**	**p-val**
age group	**18-64**	**= 0**		
inc	0.00038	0.368	-	-
$[u \rightarrow r]$	0.09474	0.186	-	-
$[r \rightarrow u]$	-0.02369	0.003	-	-
teta	0.08506	0.000	-	-
jdr	-0.45098	0.265	-	-
men	**18-64**	**= 0**	**= 18-64**	**= women**
inc	0.00042	0.187	0.920	0.026
$[u \rightarrow r]$	0.05427	0.051	0.144	0.011
$[r \rightarrow u]$	-0.01818	0.187	0.689	0.011
teta	0.03767	0.000	0.000	0.549
jdr	-0.26575	0.458	0.603	0.166
women	**18-64**	**= 0**	**= 18-64**	**= men**
inc	-0.00043	0.467	0.170	0.149
$[u \rightarrow r]$	0.12468	0.000	0.317	0.019
$[r \rightarrow u]$	-0.05320	0.004	0.111	0.058
teta	0.04285	0.000	0.000	0.527
jdr	-0.76331	0.054	0.431	0.210

Note: Seasonally adjusted monthly data for 284 municipalities, estimation period 1992:7-2002:9, R2 = 0.051, the effects of common time dummies are removed prior to estimation. The within-group estimator is used. The column denoted "p-val = 0" shows the p-value for the test of a zero long run effect. The column denoted "p-val = 18-64" shows the p-value for a test of the hypothesis that the estimated long run effects are equal to the effects for all participants. The column denoted "p-val=women" and "p-val=men" shows the p-value for tests of the hypothesis that the estimated long run effects are equal to the effects for female and male participants, respectively. The p-values are calculated using the delta-method.

In general, the coefficients for the lagged labor-force participation are significant and small, around 0.05, see Table 7 in Appendix B, where the estimates of the coefficients in front of the lagged levels of the variables are presented. The models are estimated on the basis of monthly data, so the relatively slow adjustment to the long run refers to months. The R^2 values are low, around 0.05, probably reflecting the effects of removal of the common time dummies prior to estimation.

The estimated long run effects[20] are presented in Table 3. The point estimates of *income* are imprecisely, and not significantly different from zero. The point estimates are positive, as expected in the joint model and in the male model, but negative in the model for women. The point estimates of the effects of the flow rates into programs, $[u \rightarrow r]$, are positive, as expected. They are significant in the separate models for men and women, but insignificant in the joint model. The estimated effects of outflow, $[r \rightarrow u]$, from programs are negative, as expected, and significant in the joint and the female model but insignificant in the male model. The estimated effect of *teta*, labor market tightness, is positive and significant in all equations. The estimated effect of the job destruction rate, *jdr*, is negative, as expected, but only significant in the equation for female labor-force participation.

The effects in the male and the female models are not significantly different from the effects in the joint model, except for the effect of *teta*, labor market tightness. The point estimate of *teta* is larger in the joint model than in the separate models for men and women. The standard errors for the effects are low in all three equations. The estimated effect of *teta* for men and women is significantly different from the joint model but they are not significantly different from each other. The effects of the flow rates to and from labor market programs, $[u \rightarrow r]$ and $[r \rightarrow u]$, are significantly different for men and women. The effect of income for males is significantly different from the insignificant and negative effect for women. The other effects are not significantly different between men and women.

To summarize the results so far, the long run effects of *income* are small and insignificant. The inflow rates into programs, $[u \rightarrow r]$, have the expected positive effects in all models, and the outflow rates, $[r \rightarrow u]$, have the expected negative effects. The estimated effects of the labor market tightness, *teta*, are positive, as expected. The estimated effects of the job destruction rate, *jdr*, are negative, as expected.

The point-estimate of *jdr* is relatively large, but not significant. The theoretical variable that is represented empirically by the job destruction rate is negative employment shocks, causing flows from employment to unemployment. The number of destroyed jobs measures the extent to which employment at the employment unit has decreased. The variable does not contain direct information about how many individuals that have left employment, which would have been a better measure here. Normally, the worker flows are larger than the job flows. The job destruction rate is an imperfect

[20] The long run effects are calculated from the coefficient at the lagged level of the variables, divided by the coefficient on the lagged level of the dependent variable with reversed sign.

measure of negative employment shocks, and this is probably one reason for the imprecise estimate of the effects.

In order to examine whether the size of the estimated effect of the flow rate between open unemployment and labor market programs, $[u \rightarrow r]$, varies with the state of the business cycle, the long run effect of the flow rate, $[u \rightarrow r]$, is interacted with the long run effect of labor market tightness, θ. The estimation is carried out for all participants in the 18-64 age group. The coefficient for the interaction term is significant and negative. That is, the positive effect of inflow to labor market programs becomes lower when the business cycle improve, and θ increases. In other words, the size the estimated effect of the flow rate from open unemployment into labor market programs, $[u \rightarrow r]$, is countercyclical, and the expected effect is larger in downturns.

Variables measured at different local levels are used in the estimations. This could give rise to a so-called Moulton bias, which generates a downward bias in the estimated standard errors. To check for this possibility, the model is estimated with the robust and cluster option in the Stata software. Clustered standard errors are calculated both for the 100 local labor markets and for the 25 counties. The differences in the significance levels are only marginal, so the standard errors are probably not affected by the Moulton bias.

Table 4: P-values for joint tests of long-run effects of programs and all long-run effects

	joint test $[u \rightarrow r]$ **and** $[r \rightarrow u]$		**joint test all long run effects**	
age groups	**eff = 0**	**eff = 18-64**	**eff=0**	**eff=18-64**
18-64	0.012	-	0.000	-
18-64 m	0.086	0.338	0.000	0.000
18-64 w	0.000	0.262	0.000	0.000

Table 4 presents the p-values from Wald tests of the hypothesis that the flow rates from unemployment to programs, $[u \rightarrow r]$ and from programs to unemployment, $[u \rightarrow r]$ are jointly significant. Tests of the joint significance of the long run effect of all variables are also presented, together with the results from tests of the hypothesis that the joint effects differ from the effects for all participants in the 18-64 age range. The joint effects of the flow rates into and out of labor market programs, $[u \rightarrow r]$, $[r - u]$, are significant. The effects for men are not significantly different from the effect for 18-64 years old. The long run effects of all variables are jointly significant differ significantly for men and women from the effects for all participants.

Table 5: Percentage effects on the labor-force participation rate and effects on the number of participants in labor force of changes in the explanatory variables by one standard deviation

Variable	**18-64**	**18-64 men**	**18-64 women**
inc $\Delta\%$	9.8	9.5	10.4
Δlfr %	(0.4)	(0.5)	(-0.4)
Δlf	(14 773)	(12 482)	(-11 722)
$[u \rightarrow r]$ $\Delta\%$	49.1	46.3	53.6
Δlfr %	(0.5)	0.3	0.8
Δlf	(18 184)	4 984	12 725
$[r \rightarrow u]$ $\Delta\%$	46.5	41.7	53.5
Δlfr %	-0.3	(-0.2)	-0.8
Δlf	-10 011	(-3 486)	-12 820
$teta$ $\Delta\%$	80.7	78.7	82.4
Δlfr %	0.5	0.4	0.7
Δlf	18 911	7 443	10 712
jdr $\Delta\%$	159.4	159.4	159.4
Δlfr %	(1.9)	(-1.0)	-3.6
Δlf	(-64 775)	(-19 376)	-53 981

Note: For each variable, the first row shows the percentage increase, the second row the percentage effect on the labor-force participation rate, and the third row the effect in terms of the number of persons in labor force, assuming that the population is constant, at the average level during the sample period. Note that this experiment does not use steady state restrictions, so it should not be allowed to go on forever.

Table 5 presents the long run results of an experiment where each variable is increased by one standard deviation. The standard deviations are largest for the job destruction rate (160%), and smallest for income (10%).[21] The standard deviations for the flows between labor market programs and open unemployment are relatively large, around 50% for all participants. Even

[21]Note that the job destruction rate, in contrast to the other variables, is expressed in terms of employed persons in the 18-64 age range, and not for men and women separately.

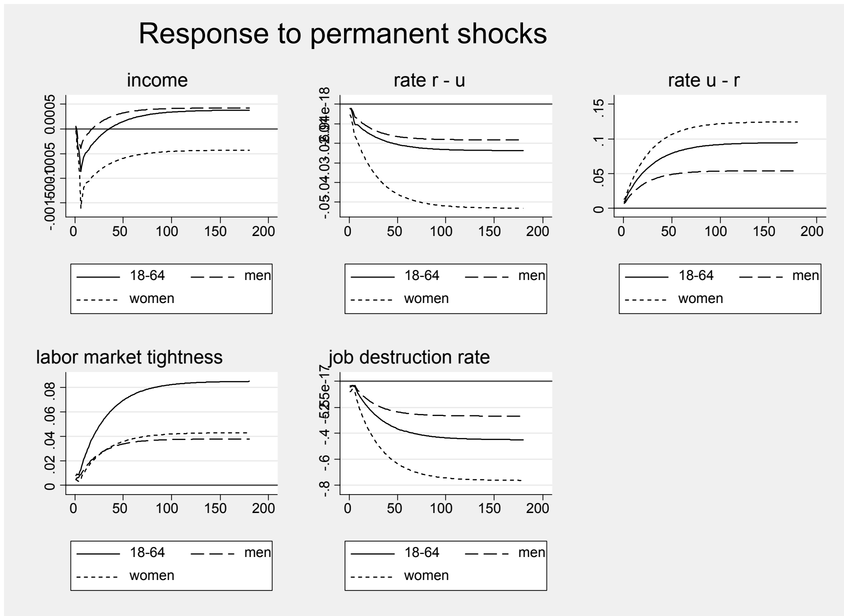

Figure 2: Response to permanent shocks, 18-64 age group

if the changes in the explanatory variables are relatively large, the percentage effects on the variables are small, reflecting the small elasticities that are estimated. Still, the number of persons that could be affected is fairly large. According to the point estimate, around 18 000 persons enter the labor force when the inflow rate to programs increases by one standard deviation. Note, however, that the estimated effect is insignificant, and the result is not significantly different from zero.

4.2.1 Short run dynamics

Figure 2 shows the graphs of the impulse-response functions for all participants in the 18-64 age range. The impulse-response functions are plots of the cumulative estimated effects, using the moving average form of the estimated models. The plots give a picture of the dynamic behavior in the models. The short run adjustment patterns are shown together with the adjustment time and the long run levels. The long run levels are the same as the long run effects in Table 3. The solid line is the response in the labor-force participation rate for men and women, the dashed line for men, and the dotted line for women.

First we can note that the long run levels are almost achieved after 110 months for all participants, so it takes around nine years to reach the long run. For all participants, most of the adjustment (75%) take place during the first 45 month or four years. Even if the estimated adjustment-coefficients are small, around 0.05, the use of monthly data means that the adjustment time is reasonable. Most of the responses to temporary shocks take place during the first six months, because the independent variables are included with seven lags. Remember that the results of experiments in which the variables are increased permanently should be interpreted with care, because no stock flow equilibrium is imposed in the estimations. The main point here is to show that the adjustment is reasonable, despite the small adjustment coefficient.

4.2.2 Comparisons with other studies

The result in this paper indicate positive effect on labor-force participation for increased flow rate from open unemployment to labor market programs. Other studies based on Swedish data, for example Essay I in Johansson (2006), Dahlberg and Forslund (1999), Wadensjö (1993) and Johansson and Markowski (1995) have also found positive effects on labor-force participation of programs in Sweden. These studies use data on stocks, the number of participants in labor market programs and in open unemployment as explanatory variables and not the flows between the stocks.

The results from models based on flows, cannot readily be compared with the results from models estimated on stocks. To see this, consider the experiment we are analyzing in this paper: "What happens to labor-force participation if we move 100 persons from open unemployment into labor market programs?".[22] Exactly the same experiment could not be carried out in a model estimated on stocks, because it is unclear which of the underlying flow rates cause the changes in the stocks when we decrease the stock of openly unemployed persons by 100 and increase the stock of program participants by 100. To see this, note that there are nine flows in the theoretical model that affect unemployment and the number of participants in labor market programs, see Figure 1. It is impossible to check which flows generate the changes in the stocks, and therefore it is not possible to compare the estimation results. Likewise, the answer to the question "What happens to labor-force participation if we increase the number of participants in labor market programs?" is straightforward in models estimated on the basis of stocks, but problematic in models estimated on flows, because we do not know which flows lie behind the changes in the stocks.

[22]The flow in the experiment has to be converted into a rate. This could be done, for example by using the average size of the stock during the sample period.

The theoretical model shows how the stocks and flows are related to each other. The expressions for the stocks are complicated functions of the flow rates[23], see Figure 1, and the other parameters in the theoretical model. Formally, this relationship could, for example, be used to determine how the stocks are affected by the change in one of the flows. To do this, values have to be assigned to the level of the flow rates and the other parameters in the expression for the change in the stocks. The average flow rates during the sample period could be used, together with assumptions about the size of other parameters involved. However, this could not be implemented because all flow rates data are not available[24]. So, even if we are prepared to accept the necessary approximations, it is not possible to calculate the effect implied on stocks using the theoretical model, because data that have to be used in the approximation are not available.

5 Summary and discussion

This study examine the question of whether the flow rate from open unemployment to labor market programs affects the labor-force participation rate. Models are estimated for participants in the 18-64 age range, and with separate models for men and women.[25] In general, the adjustment time is reasonable, it takes around nine years to reach the long run level, and most of the adjustment takes place within the first three years. Almost all long run effects have the expected signs.

The long run effect of income is positive, as expected, for all participants. The estimated long run effects of the flow rates to labor market programs from open unemployment are positive, as expected, and the effects of the flow rates from programs to open unemployment are negative, as expected. The estimated long run effect of teta, labor market tightness is positive, as expected, for all participants. The point estimates of the job destruction rate are negative, as expected, but imprecisely estimated. One reason could be that the job destruction rate is an imperfect measure of negative employment shocks.

In general, the estimated effects and elasticities are small. But the estimates indicate that the number of persons who may have entered the labor

[23]Empirically, the number of flow rates is eleven, because in and outflow from employment and outflow from programs could take place.

[24]Data are missing on the two flows between the non-participation state and employment, and on the four flows from employment or non-participation to unemployment or program participation.

[25]Estimation results for participants in the 18-24, 25-39, 40-54, 55-64, and 25-54 age groups are found in Appendix C.

force due to the increased flow rate to programs is not negligible.[26] The dominant reason for variation in the labor-force participation rate during the sample period is the job destruction rate. This effect is imprecisely estimated, however.

A "discouraged worker effect" occurs if labor force participants leave labor force when it is difficult to find a job, and return when it is easy to find work. Empirically, this effect is often estimated as a negative effect on labor-force participation due to increased open unemployment. Here, unemployment has an indirect impact due to labor market tightness - the number of vacant jobs divided by the total number of job-seekers.[27] The estimated positive effect of labor market tightness indicates that the participation rate is pro-cyclical. The negative effect of the discouraged worker effect can be counteracted by labor market programs. If programs are counter-cyclical, they reduce the business cycle variation in the labor force, and could perhaps prevent participants from leaving the labor force. The size of the estimated effect of the flow rate from open unemployment into labor market programs, $[u \rightarrow r]$, is countercyclical, so the expected effect is larger in downturns.

As may be recalled from the discussion in Section 3.3, an experiment in which the flow from open unemployment into labor market programs is increased permanently could result in a situation were all job-seekers end up as program participants. For practical purposes, the lack of steady-state restrictions in the policy experiment, which is considered here, involving changing the flow rate from open unemployment into labor market programs, is not problematic. The normal size of a policy change is probably less than one standard deviation, and the long run levels are reached after nine years. Care should be taken if the experiment involves extremely large changes in the flow rates that last for a very long time.

The estimation show that an increased probability of moving openly unemployed persons into labor market programs increases the labor-force participation rate. The point estimate for the older participants, is lower, but not significantly different from the effect for all participants. The results are robust over different age groups. All ten estimates, (including those presented in Appendix C), are positive, and two are insignificant. Moreover, the estimated effects of increased probability of entering a labor market program are similar for the different age groups. One should probably expect more differences when the different situations for participants in different age-groups

[26]The point estimates indicate that labor force could increase by 18 000 persons, if the flow rate from open unemployment into labor market programs is increased by one standard deviation, (50%).

[27]Both unemployed and participants in labor market programs are included in the total number of job-seekers.

are taken into account.[28]

The positive effects indicate that labor market programs could be used to attract more people to participate in the labor force, or alternatively to prevent people from leaving the labor force. It should be noted, that the results cannot be interpreted as a policy recommended to increase labor-force participation. This is so because the estimated effects are only partial, and no costs or indirect effects have been taken into account in the estimation.

As in Essay I in Johansson (2006), the effects on labor supply are probably over-estimated because labor market programs have been used for qualification for new periods of unemployment benefits. And, the effect is measured for the "nominal" labor force and not for the effective labor force because we do not know the search intensity for people who move in and out from labor force.

[28] The only expectation is younger participants, where the adjustment time is shorter, the effect of income is larger, the effect of the flow rates to and from labor market programs smaller, and the effect of labor market tightness smaller, compared to the other age groups.

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A Summary statistics and plots of data

Table 6 presents summary statistics for the variables in the estimations for the 18-64 age range. The total number of observations is 38 340, for 284 municipalities, and 135 monthly time periods, between 1991:08-2002:10. The variation within the municipalities, (the deviation of each municipality observation from the mean over time in each municipality), is larger than the variation between municipalities, (the deviation of the mean over time in each municipality from the total mean), for the flow rates between open unemployment and labor market programs, $[u \rightarrow r]$, and $[u \rightarrow r]$, and for labor market tightness, *teta*, implying that the time variation is more important than the variation between municipalities for these variables. The variation between and within are of about the same size for income, *inc*, and the job destruction rate, jdr. The labor-force participation rate, lf, is the only variable for which the "between" variation is larger than the "within" variation, that is the variation between the municipalities is larger than the variation over time.

The variables in the estimations are plotted in Figure 3-8. Box-Whiskers plots of the data, converted into annual frequency, are used to present both the time variation and the variation between the municipalities. The box contains data between the 25th to 75th percentiles, and the line represents the median.

Table 6: Summary statistics of the variables in the estimation, 18-64 age group

Variable		**Mean**	**Sd dev**	**Min**	**Max**
lf	Overall	0.6469417	0.0342102	0.5046371	0.7524384
	Between		0.0298625	0.5515411	0.7113511
	Within		0.0167835	0.5455315	0.7155822
inc	Overall	69.99863	9.06715	54.67853	170.6625
	Between		6.450023	63.27419	123.2307
	Within		6.384028	41.24669	117.4304
$[u \rightarrow r]$	Overall	.0858124	0.0593489	0	1.162162
	Between		0.0215451	0.0455565	0.1687584
	Within		0.0553147	-0.082946	1.12007
$[r \rightarrow u]$	Overall	0.1575314	0.1092936	0	1.391304
	Between		0.0182308	0.1100406	0.2295377
	Within		0.1077678	-0.0720063	1.395341
$teta$	Overall	0.051971	0.0753091	0	1.653846
	Between		0.0336615	0.0117152	0.227007
	Within		0.0673968	-0.1692889	1.518969
jdr	Overall	0.0167328	0.0269813	0	0.4909314
	Between		0.0028044	0.0101771	0.0364135
	Within		0.0268357	-0.0141905	0.4928846

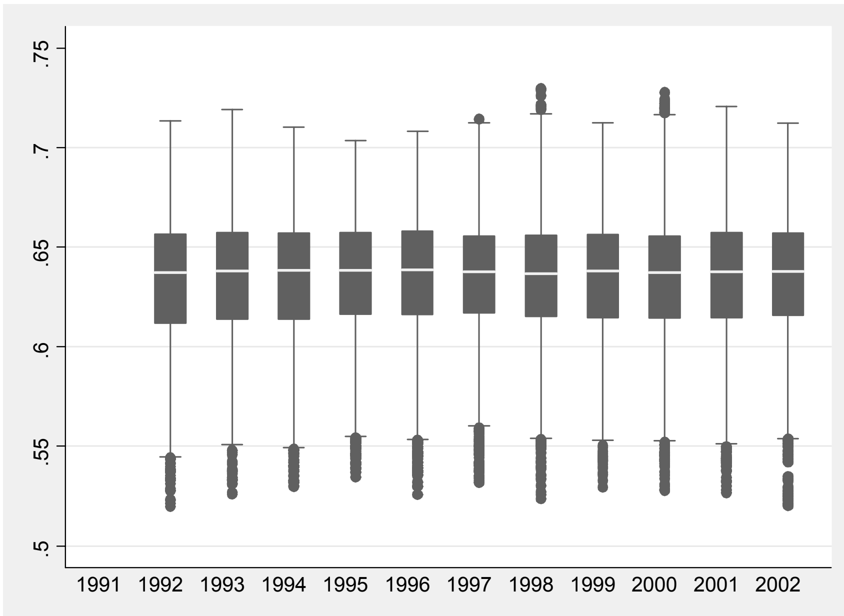

Figure 3: Labor force participation rate

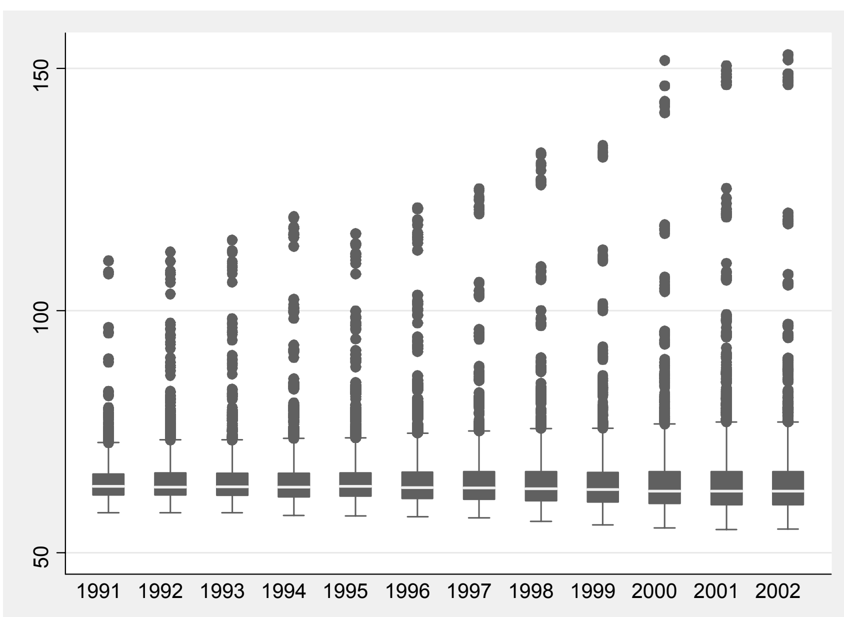

Figure 4: Income

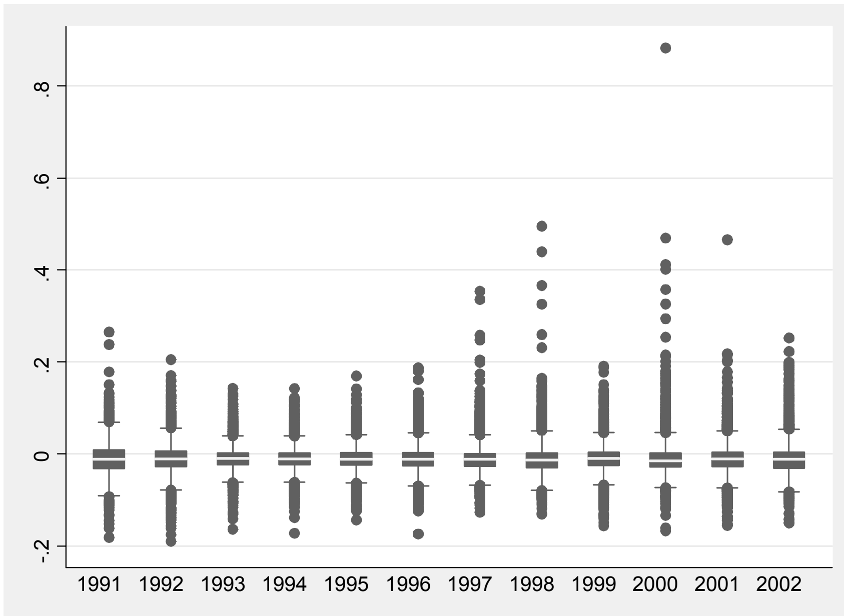

Figure 5: Flow rate open unemployment to labor market programs

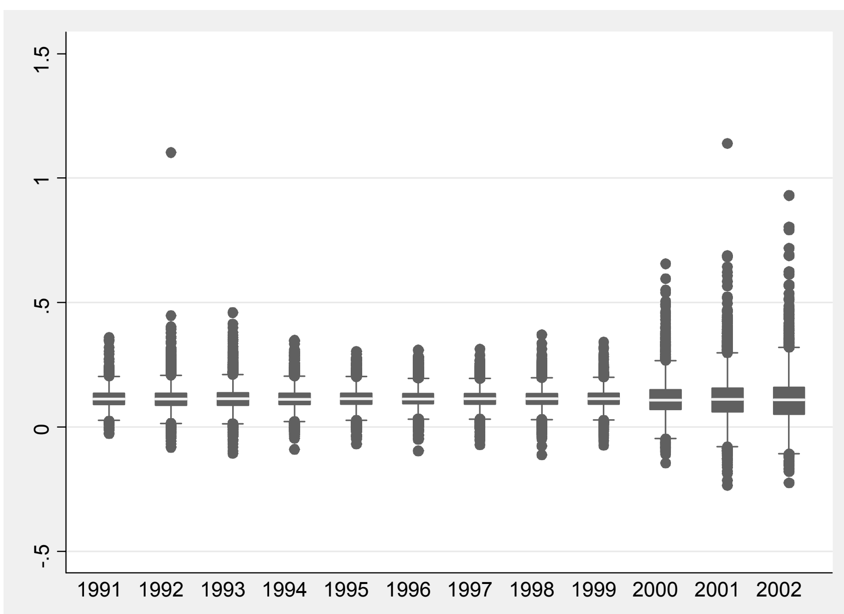

Figure 6: Flow rate labor market program to open unemployment

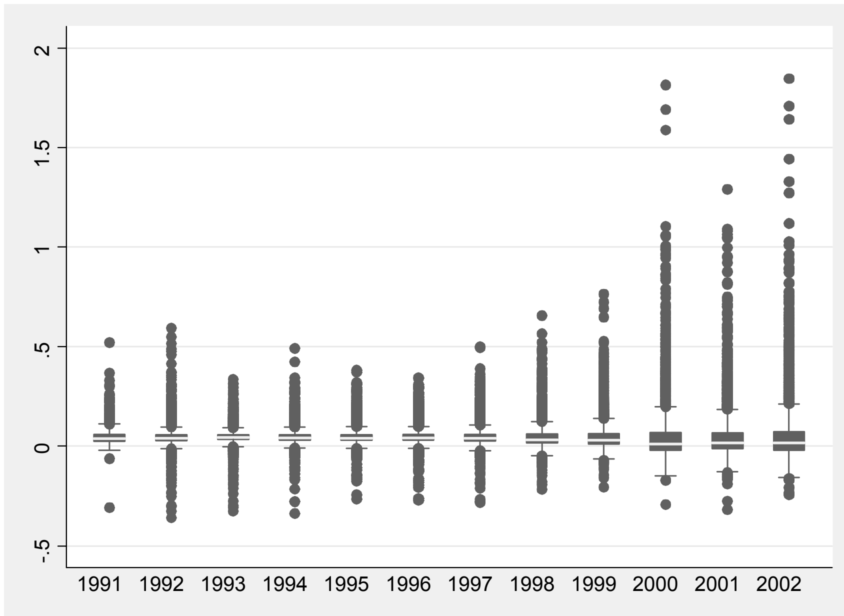

Figure 7: Labor market tightness

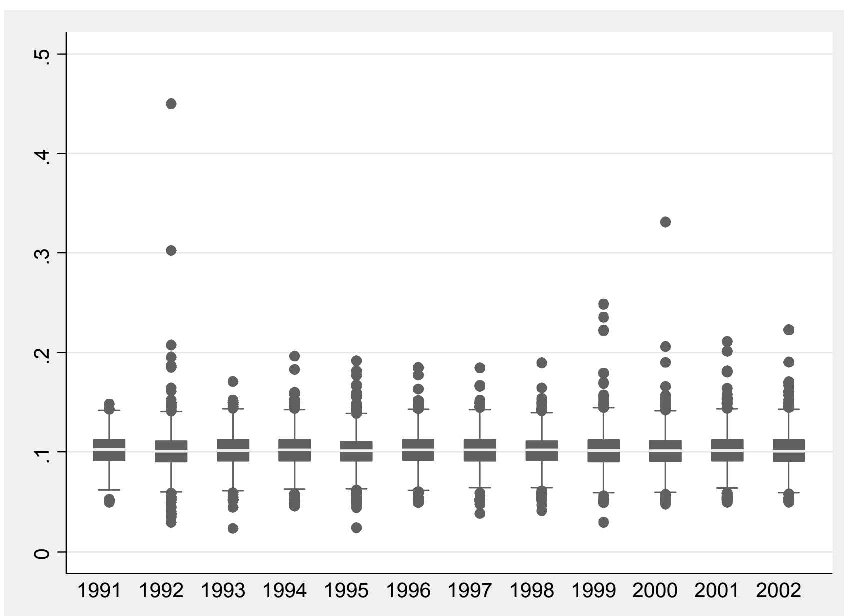

Figure 8: Job destruction rate

B Detailed estimation results

Table 7: Estimated sums of coefficients at lagged levels

Age group	**18-64**		**18-64 men**		**18-64 women**	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
lf	-0.04710	0.000	-0.06274	0.000	-0.05089	0.000
inc	0.00002	0.101	0.00003	0.270	-0.00002	0.467
$[u \rightarrow r]$	0.00446	0.003	0.00340	0.050	0.00634	0.000
$[r \rightarrow u]$	-0.00112	0.186	-0.00114	0.187	-0.00271	0.004
$teta$	0.00401	0.000	0.00236	0.000	0.00218	0.000
jdr	-0.02124	0.265	-0.01667	0.459	-0.03884	0.055
R^2		0.051		0.061		0.054
AR(1)		0.992		0.035		0.429
AR(2)		0.004		0.153		0.002
AR(3)		0.907		0.918		0.270
AR(4)		0.052		0.011		0.099
AR(5)		0.010		0.017		0.000

C Estimation results for the other age groups

In addition to the results for all labor force participants in the 18-64 age range presented in the main text, models are also estimated for participants in the 18-24, 25-39, 40-54, 55-64, 25-54, and 55-64 age groups. Separate models are estimated for the older men and women.

Table 8: Estimated sums of coefficients at lagged levels

Age group	**18-24**		**25-39**	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**
lf	-0.11062	0.000	-0.06382	0.000
inc	0.00029	0.002	0.00010	0.014
$[u \rightarrow r]$	0.00350	0.084	0.00932	0.000
$[r \rightarrow u]$	0.00600	0.571	-0.00391	0.001
$teta$	0.00106	0.000	0.00266	0.000
jdr	-0.04655	0.388	-0.02958	0.113
AR(1)		0.258		0.130
AR(2)		0.154		0.000
AR(3)		0.557		0.040
AR(4)		0.789		0.234
AR(5)		0.011		0.255

Table 9: Estimated sums of coefficients for lagged levels

Age group	**40-54**		**25-54**	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**
lf	-0.05643	0.000	-0.05525	0.000
inc	0.00003	0.066	0.00004	0.118
$[u \rightarrow r]$	0.00360	0.049	0.00812	0.000
$[r \rightarrow u]$	-0.00082	0.283	-0.00319	0.001
$teta$	0.00147	0.000	0.00410	0.000
jdr	-0.01163	0.552	-0.02239	0.182
AR(1)		0.124		0.675
AR(2)		0.223		0.006
AR(3)		0.005		0.910
AR(4)		0.858		0.194
AR(5)		0.471		0.334

Tables 8-10 present the results for participants in the 18-24, 25-39, 40-54, 25-54, and 55-64 age groups. Adjustment to the long run level is faster

Table 10: Estimated sums of coefficients for lagged levels

Age group	**55-64**		**55-64 men**		**55-64 women**	
Variable	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
lf	-0.04095	0.000	-0.05541	0.000	-0.04544	0.000
inc	-0.00006	0.045	-0.00010	0.000	-0.00011	0.012
$[u \rightarrow r]$	0.00313	0.076	0.00288	0.240	0.00431	0.013
$[r \rightarrow u]$	-0.00104	0.080	-0.00010	0.897	-0.00082	0.112
$teta$	-0.00027	0.076	-0.00033	0.005	0.00006	0.333
jdr	-0.01141	0.549	-0.01242	0.551	-0.02245	0.313
R^2		0.029		0.036		0.030
AR(1)		0.158		0.701		0.214
AR(2)		0.008		0.027		0.183
AR(3)		0.002		0.000		0.007
AR(4)		0.006		0.004		0.058
AR(5)		0.018		0.024		0.000

for the youngest participants. The estimated sum of the coefficients for the lagged dependent variable for the youngest participants is 0.90, and 0.95 for the other age groups. The model for the older participants, in the 55-64 age range, has most significant coefficients for the lagged levels of the variables. There are some signs of correlations left in the residuals, particularly for the older participants.

Table 11: The estimated long run effect for 18-24, 25-39, 40-54, and 25-54 age groups

Variable effect	**Effect 18–24**	**p-val = 0**	**p-val = 18-64**	**Effect 25–39**	**p-val = 0**	**p-val = 18-64**
inc	0.00265	0.002	0.007	0.00159	0.015	0.064
$[u \rightarrow r]$	0.03164	0.085	0.001	0.14609	0.000	0.183
$[r \rightarrow u]$	0.00542	0.572	0.002	-0.06121	0.001	0.043
$teta$	0.00956	0.000	0.000	0.04164	0.000	0.000
jdr	-0.42084	0.386	0.950	-0.46358	0.113	0.964
effect	**40–54**	**= 0**	**= 18-64**	**25–54**	**= 0**	**= 18-64**
inc	0.00049	0.065	0.699	0.00069	0.117	0.484
$[u \rightarrow r]$	0.06387	0.049	0.340	0.14698	0.000	0.173
$[r \rightarrow u]$	-0.01446	0.284	0.493	-0.05779	0.001	0.058
$teta$	0.02611	0.000	0.000	0.07416	0.000	0.427
jdr	-0.20606	0.554	0.480	-0.40530	0.182	0.888

Table 12: The estimated long run effect for the 55-64 age groups

Variable effect	**Effect 55-64**	**p-val = 0**	**p-val = 18-64**	**p-val**	**p-val**
inc	-0.00137	0.045	0.010		
$[u \to r]$	0.07641	0.076	0.671		
$[r \to u]$	-0.02548	0.080	0.888		
teta	-0.00646	0.076	0.000		
jdr	-0.27857	0.549	0.708		
men	**55-64m**	**= 0**	**= 18-64**	**= 55-64**	**= women**
inc	-0.00182	0.000	0.000	0.340	0.262
$[u \to r]$	0.05203	0.240	0.334	0.584	0.332
$[r \to u]$	-0.00174	0.888	0.102	0.077	0.225
teta	-0.00587	0.005	0.000	0.777	0.029
jdr	-0.22419	0.549	0.549	0.886	0.471
women	**55-64w**	**= 0**	**= 18-64**	**= 55-64**	**= men**
inc	-0.00235	0.012	0.003	0.292	0.572
$[u \to r]$	0.09489	0.013	1.000	0.632	0.264
$[r \to u]$	-0.01804	0.112	0.617	0.512	0.150
teta	0.00130	0.332	0.000	0.000	0.000
jdr	-0.49412	0.313	0.920	0.663	0.584

Tables 11-12 present the long run estimated effects for the 18-24, 25-39, 40-54, 25-54, and 55-64 age groups, together with p-values for tests of the hypotheses that the estimated effects are equal to zero and that they are equal to the effects for all participants in the 18-64 age range. The estimated effects of *income* are positive for all age groups, as expected, and significant, except for participants in the 25-54 age group. The effect of *income* for the 45-54 and 25-54 age groups are not significantly different from the effect for the 18-64 age group. For participants between the ages of 18-24 and 25-39, the estimated effects of *income* are greater than in the other age groups, and significantly different from the effect for all participants in the 18-64 age range. The point estimates of *income* are negative and significant for the older participants. The expected effect is positive, and the point estimates are positive for the other age groups, except for female participants age range 18-64. Appendix D indicates that low-income earners are over-represented among those who leave the labor force. Moreover, the fraction leaving the labor force in this age-group is non-trivial. This behavior introduces a negative correlation between average income and the labor-force participation rate for older persons, which shows up in the estimation results.

The estimated effects of the flow rate into labor-market programs, $[u \rightarrow r]$, are positive as expected and significantly different from zero. The effects of inflow rates, $[u \rightarrow r]$, are lower for the younger participants of age 18-24, compared to the other age groups, and significantly different compared to all participants of age 18-64. The largest point estimates are found for participants in the 25-39 and 25-54 age groups. The estimated effects of flow rates from labor market programs into open unemployment, $[r \rightarrow u]$, are negative as expected in all age groups, except for the younger participants of the 16-24 age group. The effect is not significant for participants between the 16-24 and 40-54 age groups. The effects for participants who are 25-39 and 25-54 years old are more negative and significantly different from the effects for all participants in the 18-64 age range. The effects from inflow are also larger for these age groups, indicating that they are most sensitive to changes in the flow rates in and out of labor-market programs. For the older participants, the estimated effects of the flow rates to and from labor market programs, $[u \rightarrow r]$ and $[r \rightarrow u]$, have the expected positive and negative signs, respectively, and they are not significantly different from the estimated effects for all participants.

The estimated effects of *teta*, labor market tightness are positive, as expected, and significantly different from zero. The estimated effects of *teta* are, except for the 25-54 age group, significantly different from the effects for all participants in the 18-64 age range. Labor-market tightness is measured as the total number of vacancies divided by the number of job-searchers in each age group, so the estimated coefficient measures the effect of competition for the vacant jobs within the same age group. For the older participants, the estimated effects of *teta* are significantly negative for men, and for men and women together. The point estimate for women is positive as expected, but not significant. A negative effect of labor market tightness, *teta*, implies that more people will leave labor force when it is easy to find a job. Factors underlying this estimation results are discussed in Appendix D. It turns out that it is the same factor as for the effect of income - that older participants tend to leave labor force to a larger extend than other participants.

The effects of the job destruction rate, *jdr*, are negative as expected. These effects are not significantly different from zero or from the effect for all participants in the 18-64 age range. As discussed in Section 4.2, the job destruction rate is an imperfect measure of negative employment shocks, which could be a reason for the imprecise estimates. For the older participants the estimated effects of the job destruction rate, *jdr*, are negative and not significantly different from zero. They are not significantly different from the estimated effect on all participants in the 18-64 age range.

Table 13 presents the p-values from Wald tests of the hypothesis that the

Table 13: P-values for joint tests of long-run effects of programs and all long-run effects

	Joint test $[u \rightarrow r]$ **and** $[r \rightarrow u]$		**Joint test** **All long run effects**	
Age groups	**eff = 0**	**eff = 18-64**	**eff=0**	**eff=18-64**
18-24	0.198	0.000	0.000	0.000
25-39	0.000	0.090	0.000	0.000
40-54	0.114	0.563	0.000	0.000
25-54	0.000	0.116	0.000	0.413
55-64	0.078	0.891	0.003	0.000
55-64 m	0.497	0.220	0.000	0.000
55-64 w	0.023	0.878	0.011	0.000

flow rates from unemployment to programs, $[u \rightarrow r]$ and from programs to unemployment, $[u \rightarrow r]$ are jointly significant. Tests of the joint significance of the long run effect of all variables are also presented, together with the results of tests of the hypothesis that the joint effects differ from the effects for all participants in the 18-64 age range.

The joint effect of the flow rates into and out of labor market programs, $[u \rightarrow r]$, $[r - u]$, are significant for the groups in the 25-39 and 25-54 age range, and insignificant for the 18-24 and 40-54 age groups. The effects for the 40-54 and 25-54 age groups are not significantly different from the effect for the 18-64 age range. The long run effects of each variable are jointly significant and significantly different from the effects for all participants, except for participants in the 25-54 age range. For the male older participants, the point estimates are not significantly different from the joint estimates, except for the smaller effect of the outflow rate from programs, $[r \rightarrow u]$. The estimated effects for men and women are not significantly different from each other except for the effect of $teta$, labor market tightness, as discussed above.

To summarize, in general, the effects for the youngest participants are different from the estimated effects for the other age groups. The adjustment time is shorter, the effect of income larger, with smaller effects of flow rates to and from labor market programs, and the effect of labor market tightness is smaller. The labor-force participation decision is probably very different for participants in the different age-groups. Among the younger participants in the 18-24 age group, the main alternative to labor-force participation is probably to be a student. Other important factors, specifically for the 18-24 and 25-39 age-groups, are establishing a family and childbirth. Still, the overall impression is that the estimation results are much more similar than might be expected when the different situations for participants in different age-groups are taken into account.

The main reason underlying the strange effects of income and labor market tightness for older participants is that they tend to leave labor force to a larger extent than participants in the other age-groups. This is true both for employed and unemployed, see the discussion in Appendix D.

D Discussion of the estimation results for the older participants

Some of the results for the older participants in the 55-64 age group, are odd - the parameters are precisely estimated, but the sign is the opposite of the expected. Adverse effects are found for income and labor market tightness. Tightness is the number of vacancies divided by the number of searchers, a measure that should indicate whether it is difficult or easy to find a job. Both variables are expected to have positive effects on the labor-force participation rate, but the estimated effects are often negative and significant. This section attempts to discuss possible explanations of the adverse estimation results for older participants. The aim is to informally look for indications of what factors that might underlie the estimation results.

D.1 Income

The estimated effects of income are negative and significant for all older participants, and for men and women separately. A large positive income effect relative to negative substitution effects as in an ordinary labor supply model cannot not explain the results, because here, labor-force participation is measured in terms of the number of persons and not in hours. Income is measured as average income for employed persons, and the participation rate is the number of employed, unemployed and participants in programs, divided by the number of older persons in the population. A spurious negative correlation could be introduced if average income increases due to reduced employment, and if those leaving employment also leave the labor force. The effect will be more pronounced if people who leave labor force have a smaller income than average. To be a candidate for an explanation, the effects have to be more important for the older participants than for participants in other age groups.

Individuals who are 40-54 and 55-64 years old, and employed for at least one month in $t = 0$, in the years 1990, 1991 or 1995 and not employed at least one month in $t = 1$, 1991, 1992 or 1996, respectively, were picked out from the

Table 14: Share of individuals employed for at least one month in year, t=0 and not employed for at least one month year, t=1

year	**1990-91**	**1991-92**	**1995-96**
age group	%	%	%
40-54	6.3	6.9	4.9
55-64	11.8	14.2	8.1

Table 15: Share of the individuals above registered as job-seekers in year t=0 or t=1

year	**1990-91**	**1991-92**	**1995-96**
age group	%	%	%
40-54	27.8	40.9	48.0
55-64	12.5	17.4	25.3

new database, described in Section 3.1. The average income in these groups is lower than the average income for all employed persons in the same age group.[29] The share of employed persons in these groups is larger among the older participants - between 8-14 percent, compared with 5-7 percent among participants in the 40-54 age group, see Table 10. The results indicate that the income for those who leave employment is lower than average and older participants tend to leave employment more frequently than the 40-54 age group.

If individuals in these groups (who leave employment) also leave the labor force, they should not be registered as unemployed or as participants in a labor market program in the Händel-register. The proportion of individuals in the investigated groups that are registered in Händel in any of the two years, is 13 to 25 percent for the older category, and 30 to 48 percent for the middle aged, see Table 11. In other word, the share of individuals in the investigated groups that have probably left labor force is around 75 to 87 percent for the older category, and 52 to 70 percent for the middle aged.

Data indicates that older participants who leave employment tend to leave the labor force to a larger extent than middle-aged participants. Employed persons wiht below-average income that tend to leave employment. The fact that older participants leave labor force to a larger extent than the middle

[29]The average income in 1990, 1991 or 1995 for older persons in this group was 10 998, 12 223, and 15 659. On average, the income for older employed was in 1990, 1991 or 1995 14 193, 15 213, and 18 205. The average income for 40-54 years old was 11 178, 12 547, and 15430, for the group who have left employment for at least one month in $t+1$. For those employed in $t=0$, the average income was 14 984, 16 076, and 18 805, respectively.

aged could be behind the negative correlations between income and the labor-force participation rate.

D.2 Labor market tightness

The estimated effects of *teta,* labor market tightness, are significantly negative for men, and for men and women in combination. The point estimate for women is positive, as expected, but insignificant. A negative effect of labor market tightness implies that more people will leave the labor force when it is easy to find a job. Labor market tightness is measured as the number of vacancies divided by the number of job-searchers in the age group. The estimated coefficient measures the effect of competition for the vacant jobs that take place within the same age group.

One explanation for the contra-intuitive results could be the same mechanism as for the effect of income. If older people who are registered as job-searchers in Händel leave the labor force, labor market tightness will increase and the labor-force participation rate will decrease, introducing a negative correlation between tightness and the labor-force participation rate.

Other candidates for explanations are probably not so important. Increased mortality reduces the number of searchers, and increases labor market tightness. The way in which the participation rate is affected depends on the relative effect of mortality on participants and nonparticipants in the labor force. The use of labor market programs whose purpose is to make it easier for older people to leave the labor force, might be an explanation of the pattern observed in data, especially if they are used when it is relatively easy to find a job. Two such programs[30] were introduced around 1998, after a period of extremely high unemployment rates. The effect of these programs during the sample period is, however, offset by the introduction of programs whose purpose is the opposite, to increase the possibility of getting a job among older job-searchers.[31] Programs directed at older participant are therefore not one of the main factors behind the adverse estimation results.

Job-seekers in the 55-64 and 40-54 age groups, and registered in Händel during 1992, 1995 or 1998, were picked out from Händel for furher investigation if older job-seekers leave labor force to a greater extent than other

[30]"Generationsväxlingen" where employed persons that are older than 63 years old, can if the employer permits it, retire. The vacant job should be replaced by a long-term unemployed in the 20-34 age group. Applications were allowed between January and August 1998. "Tillfällig avgångsersättning", between 1997-07 to 1998-12, permits older unemployed persons registered at an employment office to leave labor force.

[31]Public temporary work (OTA, Offentliga tillfälliga arbeten) between 1997-2001 and Special recruitment incentive (Särskilt anställningsstöd) from November 2000.

Table 16: Share of persons registered as job-seekers in t=0, and not in t=1, who have a statement of income in t=0 or t=1

year	**1992**	**1993**	**1995**	**1996**	**1998**	**1999**	**average**	
age group	$t=0$	$t=1$	$t=0$	$t=1$	$t=0$	$t=1$	$t=0$	$t=1$
45-54	89	79	79	74	77	75	82	76
55-64	85	61	70	54	69	55	75	57

Table 17: Share of persons registered as job-seekers in t=0, and not in t=1, who are registered as employed for at least one month in t=0 or t=1

year	**1992**	**1993**	**1995**	**1996**	**1998**	**1999**	**average**	
age group	$t=0$	$t=1$	$t=0$	$t=1$	$t=0$	$t=1$	$t=0$	$t=1$
45-54	57	48	47	48	48	52	51	49
55-64	51	26	34	25	39	28	41	26

job-seekers. If they do, this could result in a negative correlation between tightness and the labor-force participation rate. The job-seekers should be registered in Händel during 1992, 1995 or 1998, $t = 0$, and they are not allowed to be registered in Händel the following year, 1993, 1996 or 1999, $t = 0$. On average, 63% of the older, and 49% of the middle-aged job-seekers in $t = 0$ are not registered as job-seekers in $t = 1$.

If those who leave Händel could not be found in the employment register, it is an indication that they have left labor force. On average, 75% of the older and 82% of the middle-aged job seekers have a statement of income in the same year as they are recorded as job-seekers. The year after, on average 57% of the older and 76% of the middle-aged job seekers have a statement of income, see Table 12. The share of job-seekers with no statement of income in either of the two years is 34% for the older group and 21% for persons in the 40-54 age group. If, instead, we look at employment, the share of job-seekers registered as employed for at least one month is larger for the 40-54 age group compared to the 55-64 age group. The proportion decline between the first and the second year for the older age group, and is approximately the same for job-seekers in the 40-54 age group, indicating that older participants tend to leave labor force to a greater extent than the middle-aged.

To summarize, older job-seekers seem to leave labor force to a greater extent than job-seekers that are 40-54 years old. This could explain the negative correlation between tightness and labor-force participation rate in the estimation.

Essay III
Common trends in exports*

1 Introduction

In the empirical macro economic literature on trade, a great deal of attention has been paid to the sizes of price and income elasticities in foreign trade (see the overview in Goldstein and Kahn (1985)). The determinants of foreign trade in theoretical models are well understood, both in versions of the Hecksher-Ohlin-Samuelson-model with homogeneous goods (see Dixit and Norman (1980)), and in models with imperfect competition (see Helpman and Krugman (1985)). Empirical work on macroeconomic trade flows has little connection with trade theory. A common approach is to estimate a demand relation under the assumption that the goods are differentiated between countries. The exogenous variables in the export demand function are relative prices and a measure of income. Sometimes a supply relation is estimated simultaneously with the demand function. The specification of the supply function is often ad hoc and therefore it is unclear what the included variables are supposed to represent. For example, the role of the home market and the market structure are often vague.

Typical outcomes[1] from the empirical analyses are that relative prices matter for exports over a period of two or three years, and that about half of the quantity adjustment take place within a one year period, whereas the effect of income on exports is immediate. Put differently, the short-run price elasticity of demand is considerably lower than the long-run elasticity.

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[1]Goldstein and Kahn present a summary of estimated elasticities for exports and imports, from the most cited studies since 1973.

The interpretation made by Goldstein and Kahn is that traders will not be on their long run demand functions due to adjustment costs or incomplete information.

It follows that static trade models are not consistent with these data properties. A possible conclusion is that a dynamic structural model should be examined. One drawback of a dynamic model is that it could be hard to provide a satisfactory economic explanation of all correlations in the data. Since there is considerable uncertainty about which economic forces are behind the short-run dynamics, I will not attempt to explain them. Instead, I take the viewpoint that a simple economic model could have something to say about the *long-run* relations in data. Some relevant aspects of the behavior in data seem to be captured in the earlier estimations. Goldstein and Kahn (1985) report that the empirical evidence does not show any indication that there have been dramatically changes in the size of the estimated price and income elasticities over different time periods. The stability of the parameters suggests that it could be meaningful to use a standard model when describing the long-run behavior in trade flows.

The purpose of this paper is to analyze the long-run behavior of Swedish exports and export prices. The idea is to use the same type of underlying theoretical model as in conventional estimations, but translate the economic model into restrictions on the long-run behavior in a multivariate time series model. The long-run relations are described by the so called cointegrating vectors, and if variables are cointegrated, they contain fewer stochastic trends than the number of variables. The sources of fluctuations are the shocks to the common stochastic trends.

Two major questions will be addressed: *First*, are the predictions from the economic model regarding the cointegrating properties consistent with data? *Second*, what are the effects of exogenous shocks in the long run? In a single equation model the second question could not be answered since a particular disturbance will often affect both exports and prices. This question can, however, be addressed in a common trends model. The cointegrating vectors together with some identifying assumptions allow me to identify the trends and give them an economic interpretation, such as productivity etc.

In this paper I will estimate a common trends model for Swedish exports of manufactured goods. The following variables are included in the model: Swedish exports, foreign expenditure, relative prices and real wages. A simple two-country model is used to describe the economic behavior in the long run. The model is used to generate predictions about the cointegrating vectors. Productivity and labor supply are exogenous in the model, and they will represent the common stochastic trends. The solution to the theoretical model is used to derive the theoretical long-run responses and, hence, yield implications for the identification of the trends.

The outline of the paper is as follows. In section 2 the economic model and the results from comparative statics are reported. In section 3 the data is discussed and the estimation of the underlying VAR is presented. Section 4 contains the cointegration analysis. In section 5 the theoretical long-run responses in the endogenous variables and the identifying assumptions are presented together with estimates of the common trends model, the impulse response functions and the variance decomposition. Section 6 contains some concluding remarks.

2 The economic model

2.1 Background

In this section a model for two trading countries is presented. The model generates predictions about the cointegrating vectors and it allows me to identify the long-run responses from shocks to the common trends. The results from the model will be used in the empirical analysis of Swedish exports.

As shown in Figure 1, where exports and industrial production in twelve OECD countries are plotted, one characteristic of data is that trade seems to grow faster than income. This could be explained by systematic differences in the income elasticity between traded and nontraded goods. Thus, the observed pattern in data could then be explained by a higher income elasticity for traded goods. However since nontradeables consists to a large extent of production of services, another reasonable assumption could be a higher income elasticity for nontradeables. Another factor that causes trade to grow faster than income is slower productivity growth in the production of the nontraded goods, leading to a secular decrease in the relative price of tradeables.

A standard way to model the demand side in foreign trade is to use the elasticity of substitution framework or what is sometimes called the Armington assumption, which relies on the separability of the CES utility function. Goods with the same elasticity of substitution, σ, are grouped together in the utility function, and hence it is possible to separate the demand for goods which has the same σ. In Armington (1969) goods within the same group differ from each other depending on in which country they are produced.

2.2 The model

Consider two countries that trade with each other, and who produce one tradeable and one nontradeable goods each. The tradeable goods are differentiated from each other, and the product type produced in each country is taken as given. Suppose that the (representative) consumer's utility function is separable between traded and nontraded goods. Let the subutility for traded goods be of the CES type and nested with the utility of nontraded goods in a Cobb-Douglas function. Furthermore, let the supply side be as simple as possible with an exogenously given production factor, labor, and constant returns to scale in both sectors. There is a large number of identical firms and individuals in each country and they take prices as given.

The production function for the tradeable good is $Q_t = \theta L_t$, while the production function for the nontradeable goods is $Q_n = \lambda L_n$, where L is total labor supply, L_t employment in the nontrading sector and, L_n employment in the nontrading sector. θ and λ affect the productivity in the different sectors. The aggregate utility function is

$$U = U_n^{1-\gamma} U_t^{\gamma}; U_t = \left[\sum_{j=1}^{2} \alpha_j q_j^{\rho} \right]^{1/\rho}; U_n = q_n, \tag{1}$$

where q_1 and q_2 denote consumption of traded goods and q_n is consumption of the nontraded goods. Maximizing the aggregate utility in (1) subject to the budget restriction for the whole economy, yields the total demand in country i for traded goods j:

$$Q_t^{i,j} = \frac{\alpha_j^{-\sigma} p_j^{\sigma}}{\sum_{j=1}^{2} \alpha_j^{-\sigma} p_j^{\rho\sigma}} \gamma M^i = \alpha_j^{-\sigma} p_j^{\sigma} P_m{}^{-\sigma} U_t^i = \alpha_j^{-\sigma} \left(\frac{p_j}{P_m} \right)^{\sigma} \frac{\gamma M^i}{P_m}, \tag{2}$$

and the demand in country i for nontraded goods:

$$Q_n^i = \frac{(1-\gamma) M^i}{P_n^i}. \tag{3}$$

M^i is the nominal expenditure in country i, γ the fraction of income spent on tradeables, $P_m = \left[\sum_{j=1}^{2} \alpha_j^{-\sigma} p_j^{\rho\sigma} \right]^{1/\sigma\rho}$ the price index in the market for traded goods, p_j is the price of the traded goods j, and P_n^i is the price of nontraded goods in country i. The utility from consumption of traded goods is the expenditure on tradeables deflated by the price index for traded goods, $U_{tr}^i = \gamma M^i / P_m$. $\sigma = 1/(\rho - 1) < 0$, is the elasticity of substitution.

The setup of the model follows the treatment in Dixit and Norman (1980). Equilibrium is characterized by the national income identity in each country and by the market-clearing equation for the traded goods. (For more details about the equilibrium conditions see appendix.) These three equations give the solution for the utility levels in both countries and the relative price of tradeables. Real wages and prices of nontraded goods are obtained through the zero-profit conditions for tradeables and nontradeables. The labor supply is allocated between the two sectors in line with the Cobb-Douglas assumption. There are six exogenous variables, the factor supply and the productivity level in both sectors in each country, (L^i, θ^i and λ^i, $i = 1, 2$). These exogenous variables will, in the empirical analysis, be interpreted as the common trends.

To avoid the case of immiserizing growth, i.e. when growth results in lower real income, it is necessary to put restrictions on σ, the elasticity of substitution between traded goods. To ensure that growth will be beneficial I assume that $-\sigma$ is greater than the exported volume relative to the total production of tradeables. Since the utility function is homothetic, it is separable between nominal income and a function of prices and the utility can therefore be expressed as the nominal income deflated by a price index containing prices of all goods which are consumed. The utility level could then be thought of as a general measure of real income.

2.3 Results from the economic model

The exogenous variables in the model, productivity and labor supply, will in the empirical analysis represent the common stochastic trends. In this section I will briefly discuss the signs of the theoretical effects from changes in the exogenous variables. The results from the economic model will be used to evaluate the signs of the coefficients on the common trends. In section 5, I will use a linearized version of the model when I attempt to identify the trends. The two countries in the model are referred to as the home country and the foreign country.

In Table 1 the results from the comparative statics are summarized. The Cobb-Douglas nesting in the utility function (1) implies constant expenditure shares on traded and nontraded goods. A change in productivity in the nontrading sector will only affect the relative price between traded and nontraded goods, but it has no effect on the relative price between traded goods in the two countries. Hence we can disregard the effects from a productivity increase in the nontrading sector when we look at the trading sector. Since the focus is on the exporting sector I will not comment on the effect on the other variables. The effects which are omitted in the discussion are reported in Table 1, although the discussion only refers to exports.

An increase in the *labor supply* in the home country, L^H, results in increased production, Q_T^H, and a lower relative price in terms of the foreign traded goods, P_T^H/P_T^F. The real wage in terms of the domestic traded goods, W^H/P_T^H, is unchanged due to the assumption of constant marginal productivity, but falls in terms of the foreign goods. The foreign country substitutes for the traded goods produced at home which leads to an increase in exports, X_T^H.

Next, an increase in the *productivity* level in the trading sector in the home country, θ^H, results in more production, Q_T^H, and a lower relative price against the foreign traded goods, P_T^H/P_T^F. The real wage in terms of the price of the domestic traded goods, W^H/P_T^H, increases when the productivity increases, since labor demand is affected. The foreign country substitutes in favor of consumption of traded goods produced in the home country so exports, X_T^H will increase. The qualitative difference between a labor supply shock and a productivity shock is in the effect on the real wage.

From the home country's view it does not matter whether foreign productivity or foreign labor supply changes since the effect on exports is the same. Finally, *foreign* shocks, L^F and θ^F, in the trading sector raise the home country's price relative to the price of the foreign traded goods. The income effect in the foreign country leads to an increase in the home country's exports, X_T^H.

To summarize, the effects in the home country from foreign shocks in the trading sector are the same no matter what type of shock and the only difference between the domestic shocks is in the response of the real wage.

The discussion above refers only to the signs of the effects. The size will depend on the relative size of the countries, i.e. on each country's share of total income. If a country is small, its effect on the market price for traded goods is small. The model is formally built on two countries, but nothing prevents the interpretation that one of the countries is an aggregate of several trading partners.

3 Data and the statistical model

In the previous section we discussed how exports, relative prices and real wages react to exogenous changes in labor supply and productivity. For the empirical analyses below, we shall treat these results as the long-run predictions of the economic model and translate them into restrictions on a multivariate time series model. In this section I begin by describing the underlying statistical model. Next, I will discuss the choice and definition of variables. Finally, I discuss the initial setup of the statistical model.

3.1 A VAR-model with exogenous variables

The statistical model used here is a so called vector autoregression, VAR, with exogenous variables (see e.g. Lütkepohl (1993)). Let y_t be a $n \times 1$ vector with endogenous variables, z_t a vector with m stochastic exogenous variables and D_t a vector with the deterministic exogenous variables, such as seasonal dummies. The VAR-system with these variables is

$$\Pi(L)y_t = \delta + P(L)z_t + \Psi D_t + \varepsilon_t, \tag{4}$$

where $\Pi(L)$ is a $n \times n$ matrix polynomial of order p, that is, $\Pi(L) = I_n - \sum_{j=1}^{p} \Pi_j L^j$; and $P(L)$ is a $n \times m$ matrix polynomial of order q, $P(L) = \sum_{j=0}^{q} P_j L^j$. The VAR is written on a reduced form and no interpretation of the coefficients will be done.

3.2 Theoretical variables

The economic model should give predictions about the choice of the endogenous variables, y_t, needed to describe the exporting sector. Since productivity shocks in the nontrading sector do not affect trade, one only has to pay attention to the tradeable sector. Theoretically production is determined by the exogenous variables, and therefore sufficient to consider the demand for tradeable goods. Nothing prevents inclusion of other variables, however for my purpose I want to keep the number of endogenous variables to a minimum. I will therefore leave out the supply side and the domestic market for traded goods. Labor shocks and productivity shocks differ in their effect on the real wage. Productivity shocks influence the real wage, measured in the domestically traded goods, whereas labor shocks do not. In order to achieve a separation between the two domestic shocks I include the wage. The endogenous variables are then the exports volume, the real foreign expenditure on traded goods, the relative price and the real wage.

3.3 Aggregation of foreign demand

There are two countries in the model where one of them can be thought of as an aggregate of several trading partners. By constructing the aggregated foreign demand (see Appendix A) one obtains

$$X \approx \left(\frac{P_x}{P_m}\right)^{\sigma} \frac{\gamma M}{P_m}, \tag{5}$$

where X denotes Swedish exports, P_x the Swedish export price, P_m the market price on traded goods and $\frac{\gamma M}{P_m}$ the real expenditure on traded goods in foreign countries. σ is the elasticity of substitution in the utility function. The price elasticity of demand is $\sigma - (1+\sigma)\varpi$, where ϖ is the average share of Swedish goods in the market. The price and substitution elasticities differ because the Swedish export price P_x, is a part of the markets price P_m. If the Swedish market share is small, the difference between the price and substitution elasticities is small, and therefore I will not make a distinction between them.

3.4 Empirical variables

In this section the empirical choice of endogenous variables is presented. The traded goods is represented with manufactured goods.[2] The market consist of twelve OECD countries.[3] Let X denote Swedish exports, F foreign expenditure on traded goods, P_x/P_m relative prices and W/P_m real wages. In logarithms the endogenous variables are $y' = \left[\begin{array}{cccc} x, & f, & p_x - p_m, & w - p_m \end{array}\right]$.

Exports, x, are measured by Swedish exports of traded goods to twelve OECD countries. The foreign real expenditure on traded goods, f, is computed from industrial production minus exports plus imports.[4] The relative price $p_x - p_m$, consists of the Swedish export price p_x, and the market price p_m. Import prices of manufactured goods are used as an approximation of the imported part of p_m. Producer prices are not available at this level of aggregation and the export price is therefore used instead of the domestic price. P_m is constructed by using the geometric weighting formula with the Swedish export shares ω_i. The Swedish real wage, $w - p_m$, is constructed by using a weighted average of wage costs for blue and white collar workers in the manufacturing industry. Relative prices and real wages are measured in Swedish currency. How to construct f and p_m are shown in appendix A. The exact definitions of the variables are given in appendix B. The dataset consists of not seasonally adjusted, quarterly observations from 1972 to 1992.

The modeling approach used here assumes that the endogenous variables are integrated of order zero or one. By examining Figure 2, that contains plots of the variables, one can see that x, f and $w - p_m$ look nonstationary. Relative prices, on the other hand, look as if they could be stationary.

[2]The definition of traded goods depends on the availability of data. More specifically, I use industrial goods and exclude agriculture, mining, quarrying, food, pulp, saw mills and non-ferrous metals. See appendix for exact definition.

[3]These countries are Canada, the US, Japan, Belgium, Denmark, Finland, France, Germany, the Netherlands, Norway, the United Kingdom and Italy.

[4]This quantity is sometimes called "apparent consumption".

3.5 Estimation of the VAR-system

In addition to the endogenous variables, one stochastic exogenous variable, the effective exchange rate[5], is included in first differences of the log. It is needed to account for arch-effects and signs of non-normality in the system. The model also includes centered seasonal dummies and a constant allowing for deterministic trends.

Different information criteria and multivariate mis-specification tests are reported in Table 2. The lag order determination were troublesome in this dataset. The maximum order was set to $p = 8$, and the exogenous variable was included with the same number of lags as the endogenous. Both the log criterion (SC) and the iterated log criterion (HQ) prefer a small model with $p = 1$. The Akaike criterion does not reach a minimum within the chosen maximal order. For $p = 1$ the hypothesis of normality is rejected due to excess kurtosis, but with more lags it is accepted. The multivariate Portmanteau statistic is calculated for fifteen correlations. There are no signs of serial correlation in the residual for three and four lags. The LR tests for lag order determination, are presented in Table 3. The outcome of the LR test is $p = 2$ if one starts with a small model, and $p = 8$ if one starts with the largest model. The two consistent information criteria prefer a small model, in the same time as the results of the LR-test show that the lag order is indeterminate. I choose $p = 3$ since it is the smallest model where the residuals seem to be uncorrelated.

The modulus of the inverse roots to the polynomial $\Pi(L)$ are all less than one indicating that the system may be stable.[6] The largest modulus is 0.99 and it is followed by a double root, with a modulus of 0.93. This suggests that there could be at least one unit root in $\Pi(L)$.

4 Cointegration

A cointegrating relation is a linear combination of nonstationary variables that is stationary, (see e.g. Engle and Granger (1987)). If the variables are trending, where part of the trending behavior comes from stochastic trends, and a linear combination of the variables is stationary, it must mean that the cointegration vector cancels out the effects from the trends. Hence the trends are shared by the variables, i.e. they are common.

[5]The weights in the calculation of the effective exchange rate measure the importance of each country as a competitor to Sweden, see appendix B.

[6]Stability means that the dynamic system described by $\Pi(L)$ will revert back to the old steady state after a shock.

To see what cointegration implies for the VAR-system, reformulate the polynomial $\Pi(L)$ in (4) in order to get (apart from the deterministic variables)

$$\Gamma(L) \bigtriangleup y_t = \delta - \Pi(1)y_{t-1} + P(L)z_t + \varepsilon_t, \tag{6}$$

where $\Gamma(L) = I_n - \sum_{j=1}^{p-1} \Gamma_j L^j$ and $\Gamma_j = -\sum_{i=j+1}^{p} \Pi_i$ for $j = 1$ to $p-1$. If $\Pi(1)$ has full rank y_t is stationary. If $\Pi(1)$ equals zero, then y_t is nonstationary but not cointegrated. If the levels are nonstationary and the differences and linear combinations of the levels are stationary then $\Pi(1)$ has reduced rank r equal to the number of cointegrating vectors. In the error-correction representation, VEC

$$\Gamma(L) \bigtriangleup y_t = \delta - \alpha\beta' y_{t-1} + P(L)z_t + \varepsilon_t, \tag{7}$$

is $\Pi(1)$ split into two $n \times r$ matrices α and β. The columns of β contains the cointegrating vectors and $\beta' y_t$ is stationary. α is often called the loading matrix to the cointegrating relations $\beta' y_t$. β is independent of linear transformations of the VAR and can therefore be estimated within the reduced form of the VAR. With the method suggested by Johansen (1991) one can test hypotheses about the rank of $\Pi(1)$, and hence about the number of cointegrating vectors. If one knows the number of cointegrating vectors one can test hypotheses about the vectors.

4.1 Theoretical cointegrating vectors

Given the chosen dataset, the theoretical model implies that the demand function for Swedish exports should be a cointegrating vector.[7] The logarithm of the demand equation (5) is $x = f + \sigma(p_x - p_m)$. Hence, there should be one cointegrating vector $\beta' = \begin{bmatrix} 1 & -1 & -\sigma & 0 \end{bmatrix}$, where σ is expected to be negative. The variables in the demand function should then be nonstationary. The model predicts that in the long run real wages are determined by labor productivity, and thus real wages should be nonstationary since labor productivity is one of the common trends.

4.2 Estimation of β

With $p = 3$ the results from the *trace* and *max* tests for the number of cointegrating vectors are presented in Table 4. For details, see Johansen (1991) or Johansen and Juselius (1990). According to both the *trace* and

[7] The model also implies stationary expenditure shares on the two goods and a stationary wage share.

the *max*-statistics the null of no cointegration cannot be rejected at the ten percent level, but could at the twenty percent level. To check the tests robustness to changes in the sample period, recursive estimation as in Hansen and Johansen (1993), has been performed. In Figure 3 the *trace* and the *max* statistics are calculated from 1985:03. The first graph contains the computation within the R-representation, where $\Gamma(L)$, $P(L)$ and δ are held fixed and the "long-run" parameters in $\Pi(1)$, are allowed to vary. The second row contains the graph obtained in the Z-representation, where each period the whole model is re-estimated. The *trace* and *max* statistics are scaled with the critical value for the 90 percent level. A value greater than one means that the null of no cointegration could be rejected at the ten percent level. Both the *trace* and the *max* statistics seem to be roughly stable over time and hence not sensitive to changes in the number of observations. Since I have a sample covering only twenty years and the test-statistic should be compared with a simulated asymptotic distribution the test-result must be treated with some caution.[8] In what follows, I will assume that there is one cointegrating vector as predicted by the model although the test does not provide strong evidence of cointegration. The unrestricted estimate of β, normalized by the coefficient in front of exports, is $\beta^{'} = \left[\begin{array}{cccc} 1 & -1.3 & 1.4 & 0.1 \end{array}\right]$.

Conditional on one cointegrating vector tests for stationarity and long-run exclusion are presented in Table 5. According to the tests none of the variables are stationary which is in line with the theoretical model. By inspections of the plots in Figure 2 we see that the relative price is the only variable which looks as if it could be stationary.

The results of the test for long-run exclusion is that the real wage is the only variable which could be left out from the cointegration space. This is in line with theory and the estimated vector, with zero-restriction on the real wage, could be interpreted as a demand function with an income elasticity greater than one. The p-value for the restriction on the real wage is 0.44. Figure 4 contains the graph of the recursive calculations in the R-representation of the p-values for the restriction on the real wage. Figure 4 also shows the estimated coefficients in front of foreign expenditure and real wages together with 95 percent confidence bands. The asymptotic conditional standard errors, used to construct the confidence bands, are calculated as in Johansen (1992). The result (that the real wage could be left out from the cointegrating vector) is robust to changes in the sample period. When the real wage

[8]The test result is that we cannot reject non-cointegration at the ten percent level. Johansen and Juselius (1990) note that the power is likely to be low for cointegrating vectors with roots close to unity, but outside the unit circle, which motivate the use of a higher significance level than usual, for rejecting the null.

is excluded is the resulting cointegrating vector $\beta' = \begin{bmatrix} 1 & \underset{(0.15)}{-1.3} & \underset{(0.62)}{1.7} & 0 \end{bmatrix}$. (Conditional standard errors in parentheses.) The coefficients in the vector seem to be stable over time, even if they are uncertain.

According to the model the coefficient in front of foreign expenditure should be unity. The p-value for the joint hypothesis of unit income elasticity and exclusion of real wages is 0.20. The p-value for the test of whether unit income elasticity could be imposed on β when the real wage is excluded is 0.11. Figure 5 contains the graphs of the recursive calculations of the p-values for this two restrictions on β together with estimates of σ. The restrictions are accepted except for sample periods ending at 1988 and 1989. I choose to impose the unit income elasticity since the restriction is not rejected by the data. With this restrictions the estimated cointegrating vector is $\beta' = \begin{bmatrix} 1 & -1 & \underset{(0.55)}{3.1} & 0 \end{bmatrix}$, which could be interpreted as a long-run demand equation for Swedish exports. This result will be used in the common trends model.

In Figure 6, the stationary relation $\beta' y_t$, are plotted, when β is unrestricted, when the real wage is excluded and when the unit income elasticity is imposed. As can be seen, the stationary linear combinations differ not so much whether β is restricted or not.

My point estimate of the price elasticity, -3.1, is a bit larger in absolute values than the findings in Goldstein and Kahn (1985). Their "consensus estimate" of the long-run price elasticity of demand is between -1.25 and -2.5 and the income elasticity varies between one and two. Gottfries (1988) obtains a long-run demand price elasticity of -2.0, estimated on Swedish data with a dataset similar to mine. My larger long-run (partial) effect on exports from changes in relative prices could be explained by the fact that I use a different estimator.

4.2.1 Special cases of the model

Before we turn to the estimation of the common trends model it is interesting to examine some implications from special cases of the theoretical model. The most interesting case is when -σ tends towards infinity. In that case the Swedish export price cannot differ from the market price in the long-run and foreign income should not matter for the long-run development of exports. Still there should be one cointegrating vector in the dataset since in this case the relative price is stationary. The relative price looks as if it could be stationary, but the test above reject this hypothesis. Since infinite price-elasticity is a special case of the model, I test the hypothesis of stationary relative prices as a restriction on the cointegrating vector describing the demand function. The χ^2-statistics is 12.2, the p-value is 0.003 with two restrictions, then the hypothesis of stationary relative prices is rejected.[9]

With the CES utility function there exist another possibility to obtain stationary relative prices. If the average expenditure share on Swedish goods is constant, $\varpi = \sum_i \omega_i \alpha_j^i \left(\frac{P_j^{i0}}{P_m^{i0}}\right)^{\sigma\rho}$, then the relative prices are stationary. The demand function then implies that the market share $x - f$ is stationary. This special case implies two cointegrating vectors, and that all shocks that affect the trading sector are common. There are no signs of two cointegrating vectors (see the *trace* and the *max* statistics). The p-value for the test that a linear combination of x and f is stationary, without assuming a unit coefficient on f, is 0.018.

5 The common trends model

The common trends model relates the endogenous variables to the different sources of fluctuations. Granger's representation theorem establishes the connections between the error correction representation VEC, and the moving average representation VMA, (see for example Engle and Granger (1987), Johansen (1991) or Warne (1993)). My empirical analysis of the common trends model is based on Warne (1993) where it is shown how to recover the parameters in the common trends model from a VAR system restricted by the cointegrating vectors, and how to identify the stochastic trends. Except for the deterministic seasonal dummies, the common trends model is given by

$$y_t = A\tau_t + B\sum_{i=1}^{t} z_i + B^*(L)z_t + \Phi(L)\nu_t, \tag{8}$$

where

$$\tau_t = \rho + \tau_{t-1} + \varphi_t. \tag{9}$$

There are n endogenous variables in y_t, r cointegrating vectors and $k = n - r$ common trends. The $n \times k$ matrix A measures the long-run impact from the k common stochastic trends in τ_t. Similarly, the $n \times m$ matrix B contains the long-run coefficients on the stochastic exogenous variables z. Since $\beta' y_t$ is stationary while τ_t and $\sum_{i=1}^{t} z_i$ are nonstationary it follows that $\beta' A$ and $\beta' B$ are equal to zero. The A and B matrices refer to the long-run part of

[9] Perron (1989) shows that exogenous changes in the deterministic part of the trends can explain the observed nonstationarity. Since I have included the exchange rate, which is behind the major shifts in the levels of the relative prices, my results are not likely to be sensitive to his arguments.

the model. The transitory part is described by the polynomial $B^*(L)$ and $\Phi(L)$. The shocks to the trends φ_t can also influence the short-run behavior via $\nu_t' = \left[\begin{array}{cc} \varphi_t' & \psi_t' \end{array}\right]$. The transitory shocks ψ_t do not influence the long-run part of the system. Thus there are three different types of disturbances, the unobservable permanent shocks to the trends φ_t, the transitory innovations ψ_t, and the observable exogenous stochastic variables in z_t. The permanent shocks are assumed to be independent of each other and uncorrelated with the transitory shocks.

With four variables and one cointegrating vector three common trends may be identified. The economic model allows for four shocks, but from the exporting country's point of view it does not matter whether foreign productivity or foreign labor supply changes as the effects on exports are the same irrespective of the source. Hence, only a composite foreign trend can be identified. The three trends in τ_t are ordered so that the first represents the foreign trend, the second the domestic productivity trend, and the third the domestic trend in the labor supply $\tau_t' = \left[\begin{array}{ccc} \tau_{t*} & \tau_{t\theta} & \tau_{tL} \end{array}\right]$. There is also one transitory shock in the model.

5.1 Theoretical A-matrix and identification of the trends

The shocks to the trends are interpreted as shifts in the exogenous variables in the economic model, and the coefficients in the A-matrix measure the long-run impact on the endogenous variables from these shocks. It is possible to get an expression for the relations between the theoretical coefficients in the A-matrix if one solves a linearized version of the model in section 2, (see appendix A). Hence, the model has a number of implications for the relations between these coefficients. Specifically, we find that

$$\left[\begin{array}{c} x \\ f \\ p_x - p_m \\ w - p_m \end{array}\right] = \frac{1}{\sigma}\left[\begin{array}{ccc} \varpi(1+\sigma) & \sigma(1-\varpi)-\varpi & \sigma(1-\varpi)-\varpi \\ (\varpi+\sigma) & -\varpi & -\varpi \\ -(1-\varpi) & (1-\varpi) & (1-\varpi) \\ -(1-\varpi) & (1-\varpi+\sigma) & (1-\varpi) \end{array}\right] \times \left[\begin{array}{c} \tau_{t*} \\ \tau_{t\theta} \\ \tau_{tL} \end{array}\right].$$

ϖ is the average share of Swedish goods in consumption of traded goods in the foreign countries[10] and σ is the elasticity of substitution. The expected

[10] $\varpi = \sum_i \omega_i \upsilon_j^i = \sum_i \omega_i \alpha_j^i \left(\frac{P_j^{i0}}{P_t^{i0}}\right)^{\sigma\rho}$, where ω_i is the Swedish export share in country i, and υ_j^i is the share of Swedish goods in country i.

signs of the coefficient in the A-matrix, assuming $\sigma < -1$, are

$$\begin{bmatrix} x \\ f \\ p_x - p_m \\ w - p_m \end{bmatrix} = \begin{bmatrix} + & + & + \\ + & + & + \\ + & - & - \\ + & + & - \end{bmatrix} \times \begin{bmatrix} \tau_{t*} \\ \tau_{t\theta} \\ \tau_{tL} \end{bmatrix}.$$

The first column in A measures the impact from the foreign trend. Exports, foreign expenditure, relative prices, and real wages increase from a foreign shock. The second column of A measures the impact from the domestic productivity trend. An increase in productivity raises exports, foreign real expenditures and real wages but lowers the relative price. The third column corresponds to the domestic labor supply trend. An increase in labor supply raises exports and foreign real expenditures and lowers relative prices and wages. The effects from the domestic trends on the foreign variable should be small and arise only because the Swedish export price p_x, is part of the market price p_m. Note that both domestic trends reduce relative prices but they differ with respect to the response in real wages.

Three restrictions must be put on the A-matrix in the common trends model to ensure exact identification of the trends. The coefficients a_{22} and a_{23}, where a_{ij} is the (i, j):th element of A, measure how foreign expenditure responds to the domestic trends. Sweden can be regarded as small compared to the twelve other OECD countries, the average market share for Swedish goods ϖ, is calculated to 0.031 in 1980. Therefore it seem reasonable to let the long-run effect on foreign expenditure from domestic shocks be equal to zero. The restrictions are $a_{22} = a_{23} = 0$ and by imposing them the foreign trend is identified.

The question is then how to separate the two domestic trends from each other. The zero-profit condition, $\ln\theta + (p_x - p_m) = (w - p_m)$, tells us that a labor supply shock has the same effect on $w - p_m$ as on $p_x - p_m$, so that $w - p_x$ is unaffected. By imposing this condition, $a_{33} = a_{43}$, we can separate the labor supply shock from the productivity trend, which raises $w - p_x$. Such a restriction will also be an implication in more general models with a constant labor share. The zero-profit condition also predicts that $a_{31} = a_{41}$, but for computational reasons this overidentifying restriction is not imposed. As will be seen later the estimated a_{31} and a_{41} are not significantly different from each other.

To summarize, I identify the foreign trend by letting it, in the long run, be unaffected by domestic shocks ($a_{22} = a_{23} = 0$). The productivity trend is separated from the labor supply trend by using the zero-profit condition, where relative prices and real wages respond in the same way to a labor supply shock ($a_{33} = a_{43}$).

5.2 Interpretations of the trends

A change in τ_{tL}, the domestic labor supply, will affect production and prices in both sectors. But other factors can have the same effect in the trading sector as a change in total labor supply. For example, a decrease in γ, a preference shift in favor of nontradeables (e.g. government consumption), will result in less people working in the trading sector and will have the same effect as a decrease in labor supply. Without data for the nontrading sector it is impossible to distinguish between such a preference shock and a change in total labor supply. Note also that if wages are raised above the market clearing level, it is equivalent to reduced labor supply in the model. Hence τ_{tL} may capture labor supply to the whole economy, the employment in the trading sector, and changes in the wage setting behavior.

The domestic productivity trend $\tau_{t\theta}$, which theoretically represents labor productivity, may capture factors like technology shocks, accumulation of capital or changes in prices of other production factors. The foreign trend τ_{t*} will capture various events in foreign countries, primarily productivity growth and changes in labor supply.

5.3 Estimation of the common trends model

The model contains one stochastic exogenous variable, the effective exchange rate[11]. Theoretically, it should not influence the real variables in the long run. Therefore the restricted VAR, used to compute the parameters in the common trends model, is estimated with the restriction that the B-matrix is zero. The p-value of the LR-test[12] for the restriction that the exchange rate has no long-run effect is zero. Hence the test tells us that exchange rate changes may have permanent real effects.

Several devaluations, with apparently persistent effects, have taken place during the sample period. Theoretical models normally predict that nominal variables should not affect real variables in the long-run. For this reason I choose to impose this restriction in the estimation of the common trends model, although it is rejected.

5.3.1 Estimation of the A-matrix

The estimated A-matrix are reported below. The asymptotic standard errors, in parentheses, are computed as in Warne (1993). * denotes that the coefficient is significant at the five percent level. Note that the trends are

[11] See note 5 in section 3.5.

[12] For details see Jacobson, Vredin and Warne (1993).

normalized in such a way that their variances are unity. The coefficients then measure the long-run effects from a shock with size one standard deviation.

$$\begin{bmatrix} x \\ f \\ p_x - p_m \\ w - p_m \end{bmatrix} = \begin{bmatrix} \underset{(0.005)}{0.020^*} & \underset{(0.004)}{-0.007} & \underset{(0.002)}{0.018^*} \\ \underset{(0.004)}{0.019^*} & 0 & 0 \\ \underset{(0.014)}{-0.001} & \underset{(0.0012)}{0.0021} & \underset{(0.0009)}{-0.006^*} \\ \underset{(0.005)}{0.004} & \underset{(0.0024)}{0.019^*} & \underset{(0.0009)}{-0.006^*} \end{bmatrix} \times \begin{bmatrix} \tau_{t*} \\ \tau_{t\theta} \\ \tau_{tL} \end{bmatrix}$$

$$\tau_t = \begin{bmatrix} \tau_{t*} \\ \tau_{t\theta} \\ \tau_{tL} \end{bmatrix} = \begin{bmatrix} 0.32 \\ 0.30 \\ 0.28 \end{bmatrix} + \tau_{t-1} + \varphi_t$$

The significant effects are the following: a one standard deviation increase in the foreign trend increases exports by 2.0 and foreign income by 1.8 percent. Similarly, a one standard deviation increase in domestic productivity increases the real wage by 1.9 percent, while a one standard deviation increase in domestic labor supply increases exports by 1.8 percent and lowers relative prices and real wages by 0.6 percent. Note that all the signs of the significant coefficients are consistent with the predicted signs in the theoretical model. The zero-profit condition predicts that $a_{31} = a_{41} > 0$. The p-value for the Wald-test that both coefficients are zero is 0.475. Hence the zero-profit condition seems to be fulfilled concerning effects from the foreign trend. Next, a_{12} and a_{32} are significantly different from zero at the ten percent level, and show signs that are opposite to what is expected from the model. Since the Wald-test does not reject the hypothesis that both are zero, the p-value is 0.169, we can conclude that the productivity trend does not affect exports and export prices.[13]

But how is the size of the effects related to the economic model? One can use the theoretical A-matrix presented in section 5.1 to deduce the implied relations between the estimated coefficients in front of each trend.[14]

[13] The common trends model have been estimated without restrictions on the exchange rate and with an alternative identification. The results does not change when the exchange rate is allowed to have long run effects. The estimation with an alternative identification, where the zero-profit condition from foreign and labor supply shocks was imposed on relative prices and real wages, $a_{31} = a_{41}$ and $a_{33} = a_{43}$, yields also almost identical results. Foreign expenditure was allowed to follow the domestic productivity trend. The effect on foreign expenditure from a shock to domestic productivity is not significantly different from zero.

[14] Theoretically, the model predicts for example that the productivity trend, properly normalized, should yield a unit coefficient on $w - p_x$. Since the model does not yield predictions about the normalization, and since I do no want to use the estimated coefficients

Exports and foreign expenditure are both significantly affected by the foreign trend. Theoretically, the relative response in exports compared to foreign expenditure should be $\frac{\varpi(1+\sigma)}{\varpi+\sigma}$. With the estimated value of σ, -3.1, and the computed Swedish market share, ϖ, in 1980, 0.031, the model predicts that the coefficient on exports should be two percent of the coefficient on foreign expenditure. Since the estimated relation, a_{11}/a_{21}, is about one, the empirical effect on exports is much larger than the theoretical. The income effect in the foreign countries is behind the theoretical effect on exports. But even if one assumes a larger income elasticity than one, more substitutability in the utility function than estimated, and a larger market share for Sweden, the theoretical effect on exports relative foreign expenditure is still much lower than the estimated one. Generally, in models without common technology shocks, one expects domestic supply factors to be the main explanation behind the long-run growth in exports.

The productivity trend does not have any significant impact on exports in the common trends model, but it has on real wages. Theoretically, the relative response in exports compared to real wages should be $\frac{\sigma(1-\varpi)-\varpi}{1-\varpi+\sigma}$. With inserted values for σ and ϖ, the model predicts that the coefficient on exports should be about one and a half times as large as the coefficient on real wages. It is surprising that the main factor behind the development of real wages has no effect on exports. A reason for this could be that the model for the labor market is to simple, and that I try to get too much information out of data when I attempt to distinguish between two domestic trends. Naturally, the result that productivity has no effect on exports is also related to the result that the foreign trend has a large effect on exports. It could be that part of the productivity trend is not country specific, as I have assumed it to be, and that the common technology is captured by the foreign trend.

The relations between the coefficients in front of the labor trend are by construction equal to the theoretical ones.

5.3.2 The estimated trends

In practice, the estimated trends might capture other things than they theoretically should represent, cf. the discussion about interpretation of the trends in section 5.2. To find out if the estimated trends replicate the trending behavior of the variables they are supposed to represent, the trends are plotted against other variables in Figure 7. In the comparisons the estimated foreign trend is multiplied by a_{21}, the productivity trend by $a_{42} - a_{32}$, and

as measures of the theoretical variances, it is only meaningful to compare the relative size of the estimated coefficients on a particular trend with the theoretical predictions.

the labor supply trend by a_{13}.[15] The levels of the trends are adjusted to correspond to the first quarter of 1973 value of the variables they are plotted together with. All variables plotted with the trends are in logs and, where applicable, seasonally adjusted to facilitate comparison with the trends.

In Figure 7a the foreign expenditure is plotted with the foreign trend. By assumption the foreign trend will capture the trending behavior of the foreign variable.

In Figure 7b the labor productivity in the industry and $w - p_x$ are plotted with the productivity trend. The productivity trend resembles the characteristics of $w - p_x$, and it captures part of the drift in labor productivity. Note that the real wage has varied considerably, relative to productivity, implying very persistent variation in the labor share. On the other hand, the theoretical model predicts a constant labor share and this prediction was used to identify the trends.

In Figure 7c the labor trend is plotted with the labor force for the whole economy, measured in number of persons, and with hours worked in the industry. The variations in the labor trend do not seem to be driven by variations in labor force or in hours worked. In section 5.2 it was argued that the labor trend could capture changes in the wage setting behavior and that wages above the market clearing level is equivalent to a reduced labor supply in the model. In Figure 7d the labor trend is plotted with $w - p_x$. Note that there are three periods when the labor trend is rising quickly (1973, 1977, 1983) and each of them is followed by a period of relatively slow growth in real wages.

5.3.3 Impulse-response functions

The A-matrix tells us about the long-run responses in the endogenous variables from shocks to the trends. But questions about effects from the shocks in the short run, effects from the transitory shock, and how long it takes before the new long-run levels are reached could be answered in the moving average form of the common trends model,

$$\triangle y_t = \mu + B(L) z_t + R(L) \upsilon_t. \tag{10}$$

The short and long-run responses in the levels, y_t, to the permanent and transitory shocks in υ_t are based on sums of matrices in $R(L)$ in (10), and plots of these coefficients are called impulse-response functions. In Figure

[15] This means that a shock to the foreign trend of 0.01 changes foreign expenditure by one percent. A shock to the productivity trend of 0.01 changes $w - p_x$ by one percent and a shock to the labor supply trend of 0.01 changes exports by one percent in the long run.

8-11, the responses for the first ten years are plotted, with 95 percent confidence bands. Standard errors are calculated as in Warne (1993). Likewise, $B(L)$ contains the coefficients over time on the exogenous variables, z_t. Since I have made no attempt to model the process for z_t, the exchange rate, $B(L)$ does not necessarily measure the effects from a shock to the exchange rate and therefore a plot of $B(L)$ does not have a straightforward economic interpretation.

A *foreign shock* raises both exports and foreign expenditure immediately and the steady states are reached after about two years, while the effects on relative prices and real wages are not significantly different from zero. At all horizons the response in exports is about the same size as the response in foreign expenditure, probably reflecting earlier findings of immediate income effects. A *domestic productivity shock* increases the real wage and the permanent level is reached after two years. After half a year the effect on the other variables is not significantly different from zero. A *domestic labor shock* raises exports and lowers relative prices and real wages. In the long run the effects on relative prices and real wages are restricted to be equal. In the first two quarters, relative prices decreases more than real wages implying a temporary increase in the labor share.

On the whole, the short-run responses do not differ much from the long-run responses and the long-run levels are reached after about two or three years. Generally, the point estimates are uncertain.

The immediate effects from a *transitory shock* are that exports, relative prices and real wages increase, whereas foreign expenditure decreases. But the transitory shock is only important for relative prices and real wages, with significant effects the first ten quarters. The response in exports and foreign income become insignificant after one period. It is difficult to give an economic interpretation to the transitory shock, it raises relative prices more than real wages, implying a falling wage share the first two quarters. In terms of the model, a natural candidate is that the transitory shock captures shocks in the nontrading sector which has short-run spill-over effects on the trading sector.

In earlier studies, see Goldstein and Kahn (1985), the estimated short-run effect on exports from changes in relative prices is often found to be lower than the long-run effect. Differences in the implied elasticities in the short run compared to the long run could be found in the adjustment patterns to a certain shock. Possible sources behind these differences in the adjustment in exports and relative prices could be revealed from the common trends model if the short-run relation between the response in exports and relative prices differs from the estimated long-run response. The labor supply trend is the only trend where the immediate response in both relative prices and exports are significantly different from zero. No such pattern is found in the response of exports and relative prices, the implied average elasticity of exports with respect to relative prices the first year is -2.8, which is too close to the long run elasticity, -3.1, to be an explanation. The transitory shock could, however, be the explanation, since it raises relative prices while exports are unaffected (except for the first period).

5.3.4 Variance-decomposition

The decomposition of the variances shows how important different shocks are at different horizons for explaining the variability of the forecast errors. The results from the long-run variance decomposition[16] are presented in Table 6. Half of the long-run variation for exports comes from sources abroad and forty percent from the domestic labor supply trend, which reflects the same relations as the coefficients in the A-matrix. All the long-run variation in foreign expenditure stems, by assumption, from the foreign trend. The only trend that matters for relative prices in the long run is the domestic labor supply trend. Both domestic trends matter for real wages, but the productivity trend dominates. Note that the labor trend is unimportant for real wages, even if real wages and relative prices by assumption respond in the same way to a labor shock.

5.3.5 The model with stationary relative prices

Although results from the tests indicate that relative prices are nonstationary, it could be of interest to estimate the common trends model when the assumption of the existence of a long-run demand function is abandoned and export prices in the long run must follow foreign prices. For this reason I have also estimated the common trends model assuming stationary relative prices. The trends are identified in the same way as earlier. The result of this estimation is

$$\begin{bmatrix} x \\ f \\ p_x - p_m \\ w - p_m \end{bmatrix} = \begin{bmatrix} \underset{(0.006)}{0.024^*} & \underset{(0.004)}{-0.005} & \underset{(0.003)}{0.017^*} \\ \underset{(0.003)}{0.018^*} & 0 & 0 \\ 0 & 0 & 0 \\ \underset{(0.004)}{0.004} & \underset{(0.003)}{0.017^*} & 0 \end{bmatrix} \times \begin{bmatrix} \tau_{t*} \\ \tau_{t\theta} \\ \tau_{tL} \end{bmatrix}$$

The estimated coefficients in the A-matrix is not much different from the corresponding ones when the cointegrating vector represents the demand

[16]The decomposition over different time horizons is not presented, since it has to be conditioned on the exchange rate, and therefore difficult to interpret.

function. Thus the effects from the trends seem to be robust to different assumptions about relative prices and demand for exports. Exports still depend too much on foreign demand and too little on productivity, compared to the theoretical predictions.[17]

6 Conclusions

In this paper I focus on the long-run behavior of Swedish exports and export prices. A common approach in earlier empirical investigations of trade is to estimate a demand function for exports with relative prices and foreign income as exogenous variables. Typically, exports will react slowly to changes in relative prices. I use the same kind of underlying economic model as in earlier studies, but here the model is used to describe the long-run behavior. The theoretical models predictions about the long-run behavior are translated into restrictions on a VAR-system with four endogenous variables, exports, foreign expenditure, relative prices and real wages.

The first question addressed is: Are the predictions from the economic model regarding the cointegrating properties consistent with data? According to the model, there should be one cointegrating vector describing the demand for Swedish exports. The hypothesis of one cointegrating vector is not strongly supported by data, but it is not strongly rejected either, and for theoretical reasons I choose to impose the restriction of one cointegrating vector. Given one cointegrating vector, I find that all variables are nonstationary which is in line with the economic model. The restrictions on the cointegrating vector implied by the demand function are consistent with data, and the parameters in the estimated vector seem to be robust to changes in the estimation period. The resulting estimated vector can be interpreted as a long-run demand function, with unit income elasticity and with an estimated price elasticity of -3.1. The point estimate of the long-run price elasticity is a bit larger in absolute value than the findings in Goldstein and Kahn (1985), whereas the income elasticity is in line with earlier findings.

The second question addressed is: What are the effects from exogenous shocks in the long run? To answer this question I estimate a common trends model, where the exogenous variables in the theoretical model represent the common trends. I identify three shocks in the common trends model. One foreign shock, one domestic productivity shock, and one domestic labor supply shock. I find that the foreign trend and the domestic labor trend are

[17]It can be argued that the response of exports to foreign shocks should be restricted to zero, but I retain the identifications since I want to check the robustness of the results to assumptions about the demand side.

equally important for exports. The domestic labor trend matters for relative prices, whereas the productivity trend is primarily important for real wages. The empirical evidence obtained in earlier studies, of lower short-run than long-run price elasticities of export demand seems in my estimation to be captured by the response to the transitory shock. Also, earlier findings of an immediate income effects, seems to be captured by the response in exports and foreign expenditure to a foreign shock.

The signs of the significant coefficients measuring the long-run effects from the trends are in line with the theoretical model. The relative size differs, however, from the theoretical predictions. A remarkable result is that the productivity trend has no effect on exports. One reason for this could be that the model is to simple to discriminate between the two domestic shocks. I also found a surprisingly large effect on exports from foreign shocks. Generally, in models with no common technology shocks, one would expect domestic supply factors (and not foreign demand) to be the main explanation behind the long-run growth in exports.

These two major deviations from the theoretical relative responses could, however, be explained by the presence of a shock to all countries in for example technology, which in the present setting may be captured by the foreign shock. The model still implies that the demand function should be a cointegrating vector, if both common and country specific shocks are allowed, but the identification of the trends will be wrong. With this dataset it is impossible to distinguish between common and country specific shocks. But if a common shock is slow to disperse between countries, it may still be reasonable to regard country specific shocks as more important than common shocks in the medium run. Generally, objections can be raised against the interpretation of a static model as describing long-run behavior, the reason being that it does not incorporate basic features of a growth model, e.g. intertemporal decisions. Hence it is plausible that the long-run restrictions I have put on the VAR-system, should be interpreted as economic medium run restrictions. Of course, the short time span of data, twenty years, also makes it questionable that I have found "long-run" relations.

To summarize, the results from the cointegration analysis and the signs of the significant parameters in the long-run response are in line with the theoretical model. However, the relative size of some coefficients differ from the predictions in the model, and I find surprisingly large long-run effect on exports from foreign shocks and no effects from productivity shocks. Nevertheless, I think that this simple model captures some important aspects of the medium run behavior of Swedish exports and relative prices.

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A The economic model

The model and a summary of the result from comparative statics are presented in section 2. In section 5.1 the solution of a linearized version of the model is presented. Here I will present the equilibrium conditions and discuss how the solution is obtained. For the comparative statics it is enough to differentiate the equilibrium conditions, while in the empirical analyze the explicit solution is used for identification of the trends and for evaluating the relative sizes of the estimated long run responses.

The setup of the model follows the treatment in Dixit and Norman (1980). Consider two countries, the home (H) and the foreign (F) country, that trade with each other. They produce one tradeable and one nontradeable goods each. Equilibrium is characterized by the national income identity and by market-clearing in the goods and labor markets.

The national income identity for the home country is given by

$$E^h(p_t^h, p_t^f, p_n^h, U^h) = R^h(p_t^h, p_n^h, L^h, \theta^h, \lambda^h), \tag{11}$$

and for the foreign country

$$E^h(p_t^h, p_t^f, p_n^h, U^h) = R^f(p_t^f, p_n^f, L^f, \theta^f, \lambda^f). \tag{12}$$

E^i and R^i denote the expenditure and the revenue function in country i ($i = h, f$), p_j^i the price of good j produced in country i ($j = t, n$), U^i the utility in country i, L^i labor supply in country i, θ^i productivity in the trading sector in country i and λ^i the productivity in the nontrading sector in country i.

The market clearing condition for traded goods produced in the home country is

$$E_1^h(p_t^h, p_t^f, p_n^h, U^h) + E_1^f(p_t^h, p_t^f, p_n^h, U^f) = R_1^h(p_t^h, p_n^h, L^h, \theta^h, \lambda^h), \tag{13}$$

where E_k^i and R_k^i denote the partial derivatives of the expenditure and revenue functions in country i w.r.t the k:th argument. The price of the traded goods produced in the foreign country p_t^f is normalized to one.

The market clearing for nontraded goods in the home country is

$$E_3^h(p_t^h, p_t^f, p_n^h, U^h) = R_2^h(p_t^h, p_n^h, L^h, \theta^h, \lambda^h), \tag{14}$$

and in the foreign country

$$E_3^f(p_t^h, p_t^f, p_n^h, U^f) = R_2^f(p_t^f, p_n^f, L^f, \theta^f, \lambda^f). \tag{15}$$

The real wage is obtained from

$$w^h = R_3^h(p_t^h, p_n^h, L^h, \theta^h, \lambda^h), \tag{16}$$

and

$$w^f = R_3^f(p_t^f, p_n^f, L^f, \theta^f, \lambda^f). \tag{17}$$

The employment in each sector should add to total factor supply i.e.

$$L^h = L_t^h + L_n^h, \tag{18}$$

and

$$L^f = L_t^f + L_n^f. \tag{19}$$

These nine equations determine the two utility levels, the relative prices of traded and nontraded goods, the real wages and the distribution of employment in the two sectors in each country. Market clearing for nontradeables in (14) and (15), E_3^i and, $E^i = w^i L^i$ yield the employment in the nontrading sector as a fraction of total labor supply, $L_n^i = (1-\gamma)L^i$. L_t^i are solved from (18) and (19). Given the assumed utility and production functions equation (14) and (15) correspond to the zero profit conditions for nontradeables and from them p_n^i is expressed as a function of w^i and λ^i. Equations (14) and (15) are substituted into (16) and (17) to get the real wages expressed in terms of p_t^i and θ^i. In equation (13) is p_t^h a function of U^i, p_n^i, and the exogenous variables L^i, θ^i and λ^i. In equations (11) and (12) is U^i a function of p_t^h and the exogenous variables. (11), (12) and (13) are not loglinear, therefore they are linearized in logarithms to obtain the solution used to derive the A-matrix in section 5.1.

The revenue function is $R^i = p_t^i Q_t^i + p_n^i Q_n^i$, where $Q_t^i = \theta^i L_t^i$ and $Q_n^i = \lambda L_n^i$, and it is linearized around $\ln R_0^i$ by using $\ln R^i = \ln(e^{\ln R_t} + e^{\ln R_n}) \approx \ln R_0^i + \frac{R_{t0}^i}{R_0^i}(R_t^i - R_{t0}^i) + \frac{R_{n0}^i}{R_0^i}(R_n^i - R_{n0}^i)$, then $R^i \approx (R_t^i)^\gamma (R_n^i)^{1-\gamma}$.

The expenditure function, except for constants, is given by $E^i = U^i P_m^\gamma (P_n^i)^{1-\gamma}$, where $P_m = \left[\sum_i \alpha_i^{-\sigma}(p_t^i)^{\sigma\rho}\right]^{1/\sigma\rho}$. With a linear approximation of $\ln P_m$ round $\ln P_m^0$, (see next section) the expenditure function is $E^i = U^i(\prod_i (P_t^i)^{\nu_i})^\gamma (P_n^i)^{1-\gamma}$.

To solve the model, the total demand for the traded goods produced in the home country i.e. the left hand side of (13) is approximated by $E_1^h + E_1^f \approx (D_t^h)^{\nu_h}(X_t^h)^{\nu_f}$, where ν_i is the expenditure share of the traded goods produced in the home country, D_t^h is the domestic consumption of the traded goods produced in the home country and X_t^h is the home country's exports. In the A-matrix in section 5.1 the average foreign expenditure shares on Swedish goods is $\varpi = \sum_i \omega_i \nu_j^i$, where ω_i is the Swedish export share in country i and ν_j^i is the share of Swedish goods in foreign country i.

A.1 Aggregation of foreign demand

There are two countries in the model and one of them is thought of as an aggregation of several trading partners. Then we need to know how to aggregate the foreign demand functions into one. Recall from (2) that the demand for good j in country i is $Q_t^{i,j} = \alpha_j^{-\sigma} p_j^{\sigma} {P_m}^{-\sigma} U_t^i$, where $P_m = \left[\sum_{j=1}^k \alpha_j^{-\sigma} p_j^{\sigma\rho}\right]^{1/\sigma\rho}$, where k is the total number of countries. A linear approximation of $\ln P_m$ round $\ln P_m^0$ shows that it could be interpreted as a geometric price index[18].The approximation of P_m for country i with a geometric index round P_m^{i0} is then

$$\frac{P_m^i}{P_m^{i0}} \approx \prod_{j=1}^k \left(\frac{P_j^i}{P_j^{io}}\right)^{\upsilon_j^{i0}}. \tag{20}$$

The weight $\upsilon_j^{i0} = \frac{p_j^{i0} q_j^{i0}}{\gamma M^{i0}} = \alpha_j^i \left(\frac{P_j^{i0}}{P_m^{i0}}\right)^{\sigma\rho}$ is the expenditure on traded goods j in country i relative total expenditure on tradeables in the base year.

The aggregate demand equation is found by making an approximation around the log of the demanded quantity. Let $X = \sum_{i=1}^n x_i$ denote Swedish export to the n importing countries, and $\omega_i^0 = \frac{x_i^o}{X^o}$ the share of export to country i of total Swedish exports in the approximation point. Linearizing around the log of x_i we get an expression for total exports:

$$\frac{X}{X^o} \approx \prod_{i=1}^n \left(\frac{x_i}{x_i^o}\right)^{\omega_i^0}. \tag{21}$$

Let σ and γ be the same in each country and substitute the expression for

---

[18]

$$\ln P_m^i = \frac{1}{\sigma\rho} \ln \left[\sum_{j=1}^k \alpha_j^{-\sigma} p_j^{\sigma\rho}\right] = \frac{1}{\sigma\rho} \ln \left[\sum_{j=1}^k \alpha_j^{-\sigma} e^{\sigma\rho \ln p_j}\right]$$

$$\approx \frac{1}{\sigma\rho} \ln \left[\sum_{j=1}^k \alpha_j^{-\sigma} p_{j0}^{\sigma\rho}\right] + \sum_{j=1}^k \frac{\alpha_j^{-\sigma} p_{j0}^{\sigma\rho}}{\left[\sum_{j=1}^k \alpha_j^{-\sigma} p_{j0}^{\sigma\rho}\right]} \left(\ln p_j - \ln p_{j0}\right),$$

$$= \frac{1}{\sigma\rho} \ln \left[\sum_{j=1}^k \alpha_j^{-\sigma} p_{j0}^{\sigma\rho}\right] + \sum_{j=1}^k \upsilon_j^0 \left(\ln p_j - \ln p_{j0}\right).$$

Hence

$$\frac{P_m^i}{P_m^{i0}} = \prod_{j=1}^k \left(\frac{P_j^i}{P_j^{i0}}\right)^{\upsilon_j}$$

The expenditure share on good i is $\frac{\alpha_i^{-\sigma} p_{i0}^{\sigma\rho}}{\sum_{j=1}^k \alpha_j^{-\sigma} p_{j0}^{\sigma\rho}} = \frac{p_{io} q_{i0}}{\gamma M_0} = \upsilon_i^0$.

the demand (2) in each country into (21) to get

$$\frac{X}{X^o} \approx \left(\frac{P_x}{P_x^0}\right)^{\sigma} \prod_{i=1}^{n} \left(\left(\frac{P_m^i}{P_m^{i0}}\right)^{\omega_i^0}\right)^{-\sigma} \left(\frac{U_{tr}^i}{U_{tr}^{i0}}\right)^{\omega_i^0},$$

where $U_{tr}^i = \frac{\gamma M^i}{P_m^i}$. The resulting aggregate equation is

$$X \approx \left(\frac{P_x}{P_m}\right)^{\sigma} U_{tr} = \left(\frac{P_x}{P_m}\right)^{\sigma} \frac{\gamma M}{P_m}, \tag{22}$$

where P_m is the market price constructed according to (20),

$$\frac{P_m}{P_m^0} \approx \prod_{i}^{n} \left(\frac{P_m^i}{P_m^{i0}}\right)^{\omega_i^0} = \prod_{i}^{n} \left(\prod_{j}^{k} \left(\frac{p_j^i}{p_j^{i0}}\right)^{\upsilon_j^{i0}}\right)^{\omega_i^0},$$

and

$$\frac{\gamma M}{P_m} = \prod_{i}^{n} \left(\frac{\gamma M^i}{P_m^i}\right)^{\omega_i^0}$$

is the real expenditure on tradeable goods in the foreign countries.

B Data

B.1 Definitions

Manufactured goods are used to represent traded goods in the model. The definition of traded goods depends on the availability of data. More specifically, I use industrial goods and exclude agriculture, mining, quarrying, food, pulp, saw mills and non-ferrous metals. The definition of manufactured goods according to the trade statistics, SITC revise 3, is 5-9 excl 68 and 793. The definition according to the production statistics, SNI, is 32, 33excl33111, 34excl34111, 35excl353/4, 36, 371, 38excl3841and 39.

The market consist of twelve OECD-countries, Canada, the US, Japan, Belgium, Denmark, Finland, France, Germany, the Netherlands, Norway, the United Kingdom and Italy.

B.2 Calculations of the foreign variables

The weights in the calculation of foreign expenditure and on the market price are based on apparent consumption, which is defined as production minus exports plus imports. To get data I have to use different sources and my aim was to come as close as possible to the definition of traded goods. Data on value added in current prices are from *National accounts, volume 2, OECD*, Table 12, sector12-19. To convert this into production I use the ratio between value added and output from *Handbook of industrial statistics, 1988, Unido*, Table 12, SNI sector 32, 33, 34, 35excl353/4, 36,371 and 38. The value of exports and imports are from *OECD Trade Statistics*, series A, Sitc 5-9.

The Swedish exportshare ω_i, i =1..12, is the value of Swedish exports of traded goods divided by total exports of traded goods to the market.

The foreign real expenditure on traded goods in each country is computed from indexes on import, industrial production and exports. The weights are the shares of apparent consumption, constructed as below. Swedish exportshares are used in the aggregation.

The market price in each country should consist of the import price and the domestic price for the traded goods. Since producer or domestic prices are not available at this level of aggregation I have used export prices for traded goods instead of the domestic price. The shares in apparent consumption are used to combine the two price indexes and the aggregation is done with Swedish exportshares.

To compute ϖ, the average Swedish market share, for each country I use the exported value divided by the value obtained for apparent consumption. To get the average I use Swedish exportshares.

The weights in the computation of the effective exchange measure the importance of each country as a competitor to Sweden. I use data from National Institute of Economic Research on the import matrix which I adjust with the home-market share by using the weights in apparent consumption.

The Swedish wage cost is constructed by using data over wage cost for blue and white collar worker, where the wage cost for white collar worker is converted into hourly costs by the average working hours. The shares of the total wage cost bill in 1980 are used as weights.

B.3 Sources

• Exchange rates, Source: *Central Bank of Sweden*
• Swedish exports of traded goods to the twelve countries in the market, Sitc, current prices. Source: *National Institute of Economic Research, Sweden.*
• Swedish export price on traded goods, Sitc. Source: *National Institute of Economic Research, Sweden.*
• Import prices on traded goods in the foreign countries. Source: *National Institute of Economic Research, Sweden* 1975-1992, 1972-1974 from the database used by Gottfries (1988).
• Import volume of traded goods in the foreign countries. Source: *National Institute of Economic Research, Sweden* 1977-1992, 1972-1976 from the database used by Gottfries (1988).
• Export prices on traded goods in the foreign countries. Source: *National Institute of Economic Research, Sweden.*
• Export value on traded goods in the foreign countries. Source: *OECD Trade Statistics, series A, Sitc 5-9.*
• Industrial production in the foreign countries. Source: *Main Economic Indicator, OECD.*
• Labor force in Sweden. Source: *Central Bureau of Statistics, Sweden.*
• Hours worked, SNI 3 . Source: *Central Bureau of Statistics, Sweden.*
• Industrial production in Sweden. *Source: Central Bureau of Statistics, Sweden.*
• Wage costs, blue and white collar worker. Source: *Central Bureau of Statistics, Sweden.*
• Working hours for white collar worker. Source: *Central Bureau of Statistics, Sweden.*

Table 1. Comparative statics in the economic model

Change in	L^H	θ^H	λ^H	L^F	θ^F	λ^F
Q_T^H	$+$	$+$	0	0	0	0
Q_T^F	0	0	0	$+$	$+$	0
Q_N^H	$+$	0	$+$	0	0	0
Q_N^F	0	0	0	$+$	0	$+$
P_T^H/P_T^F	$-$	$-$	0	$+$	$+$	0
P_T^H/P_N^H	0	$-$	$+$	0	0	0
W^H/P_T^H	0	$+$	0	0	0	0
W^H/P_N^H	0	0	$+$	0	0	0
U^H	$+$	$+$	$+$	$+$	$+$	0
U^F	$+$	$+$	0	$+$	$+$	$+$
X_T^H	$+$	$+$	0	$+$	$+$	0
D_T^H	$+$	$+$	0	$-$	$-$	0
X_T^F	$+$	$+$	0	$+$	$+$	0
D_T^F	$-$	$-$	0	$+$	$+$	0

Note: *Q_j^i = production of traded and nontraded goods, $i = H, F$, $j = T, N$, where H and F denotes the home and foreign country and T and N denotes traded and nontraded good. P_j^i = price in country i on good j. W^i = wage in country i. U^i = real income in country i. X_T^i = exports from country i. D_T^i = domestic consumption of the traded good produced in country i. L^i = labor supply in country i, θ^i = productivity in the trading sector in country i, λ^i = productivity in the nontrading sector in country i.*

Table 2. Information criteria and multivariate diagnostics for the VAR

MODEL	1	2	3	4	5	6	7	8
INFORMATION CRITERIA								
AIC	31.69	31.82	31.67	31.81	31.63	31.73	32.93	33.01*
SC	30.46*	29.98	29.22	28.74	27.95	27.44	27.02	26.54
HQ	31.12*	31.08	30.69	30.58	30.16	30.02	29.96	29.85
MULTIVARIATE TESTS								
Skewness	0.19	0.64	0.62	0.98	0.87	0.96	0.86	0.35
Kurtosis	0.00	0.36	0.71	0.45	0.56	0.37	0.81	0.99
Normality	0.00	0.55	0.78	0.84	0.83	0.77	0.94	0.80
Portmantau 15 lags	0.007	0.044	0.175	0.206	0.061	0.021	0.001	0.000

Note: All statistics are from Lüthkepohl (1993). P-values reported for the multivariate tests.

Table 3.LR test for lag length

H_0	1 in 2	2 in 3	3 in 4	4 in 5	5 in 6	6 in 7	7 in 8
χ^2	49.8	29.0	50.2	27.0	47.6	54.5	49.9
p-value	0.0	0.088	0.0	0.135	0.0	0.0	0.0

Table 4. Test for the cointegrating rank

H_0	$trace$	$crit_{0.90}^{trace}$	$crit_{0.80}^{trace}$	max	$crit_{0.90}^{\max}$	$crit_{0.80}^{\max}$
$r = 0$	42.69	43.95	40.15	23.94	24.73	21.98
$r \leq 1$	18.73	26.79	23.64	15.71	18.60	16.20
$r \leq 2$	3.04	13.33	11.07	2.57	12.07	10.04
$r \leq 3$	0.47	2.69	1.66	0.47	2.69	1.66

Note: Critical values from Osterwald-Lenum (1992), Table 1.

Table 5. Restrictions on the cointegrating space when $r = 1$

	stationarity	exclusion
export	0.00	0.01
foreign expenditure	0.00	0.02
relative prices	0.00	0.01
real wage	0.00	0.44

Note: P-values reported.

Table 6. Long run variance decomposition

	foreign trend	productivity trend	labor supply trend
export	0.533	0.054	0.413
	(0.147)	(0.062)	(0.139)
foreign expenditure	1.00	0	0
	(0)	(0)	(0)
relative price	0.008	0.115	0.877
	(0.039)	(0.125)	(0.124)
real wage	0.044	0.770	0.086
	(0.089)	(0.083)	(0.034)

Note: Standard errors in brackets.

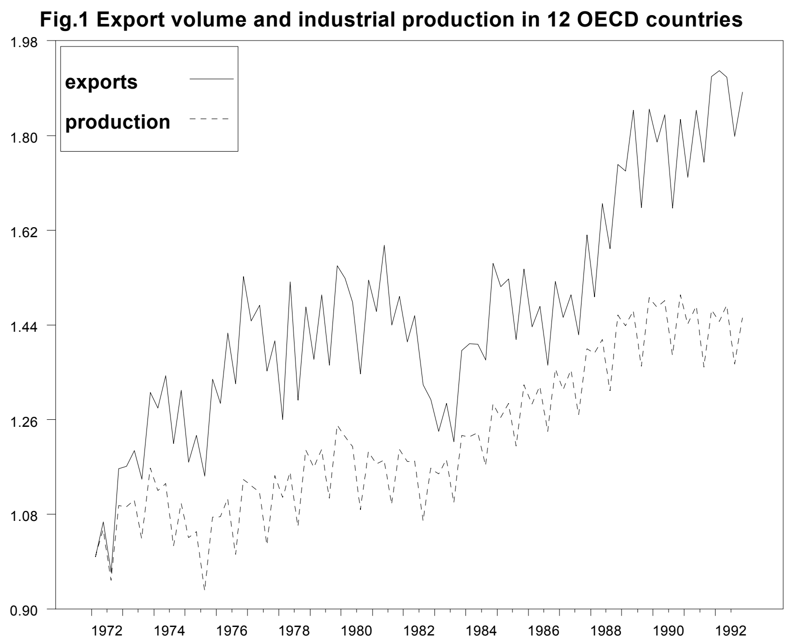

Figure 1: Export volume and industrial production in 12 OECD countries

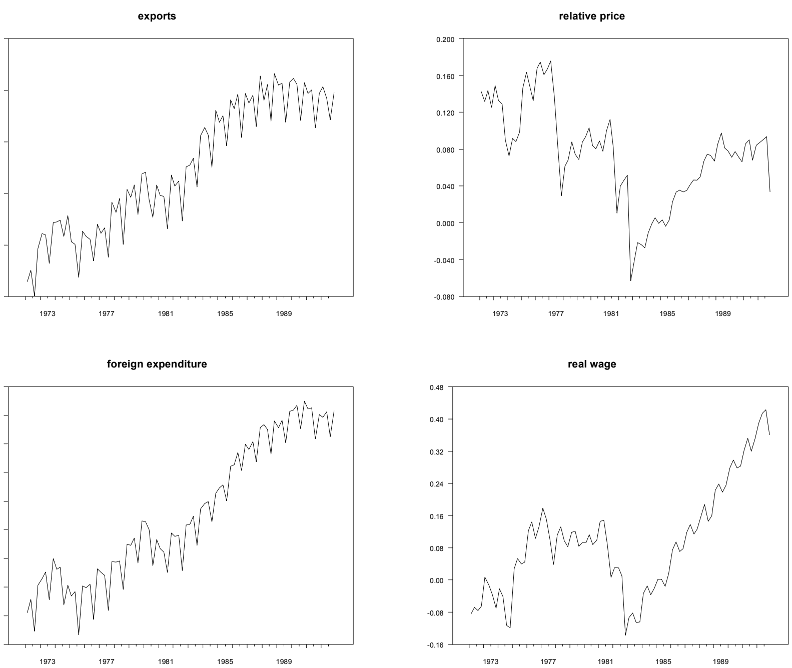

Figure 2: The endogenous variables

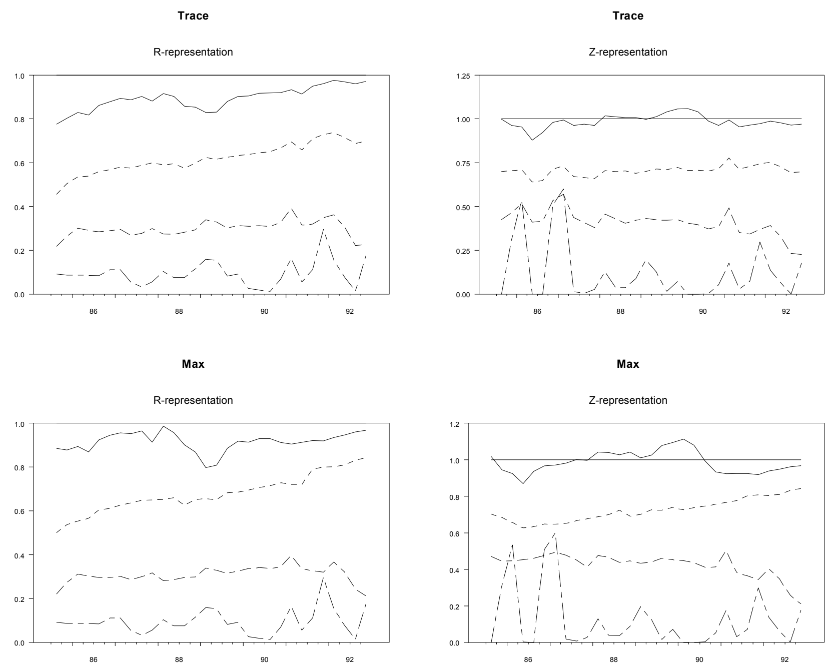

Figure 3: The trace and the max statistics, 1985:03- 1992:04

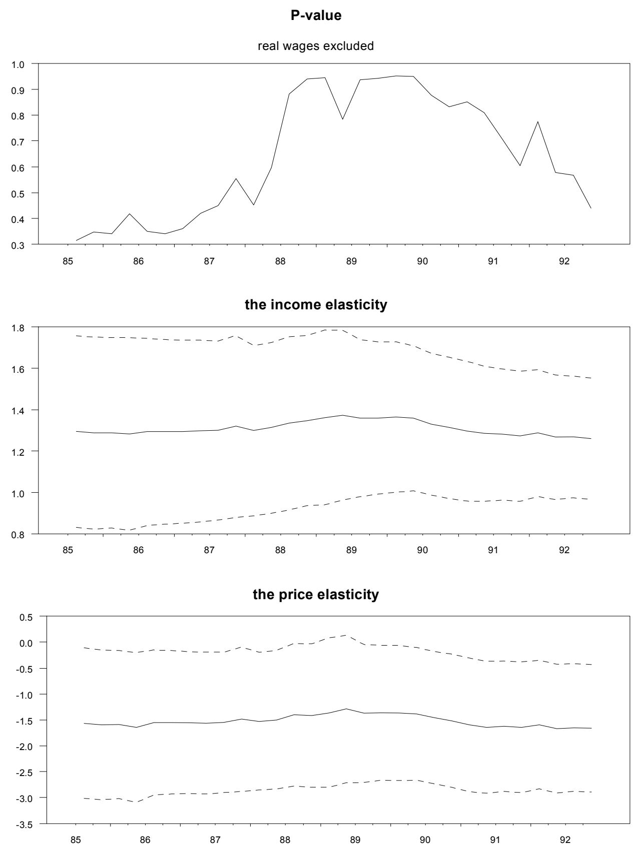

Figure 4: P-values for zero coefficient on real wages, the coefficients on foreign expenditure and relative prices, R-representation, 1985:03-1992:04

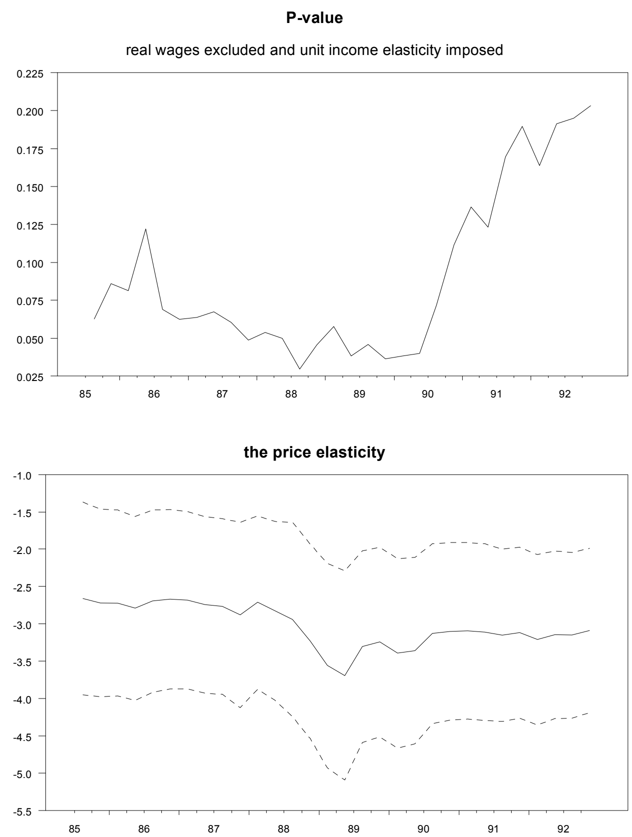

Figure 5: P-values for zero coefficient on real wages and unit coefficient on foreign expenditure, and estimated price elasticity, R-representation, 1985:03-1992:04

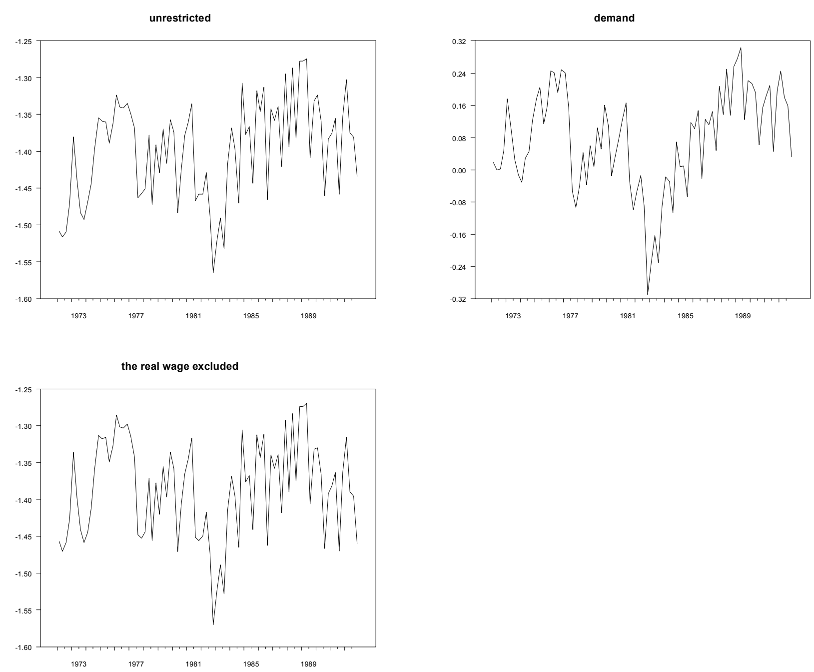

Figure 6: The stationary relations, $\beta' y_t$

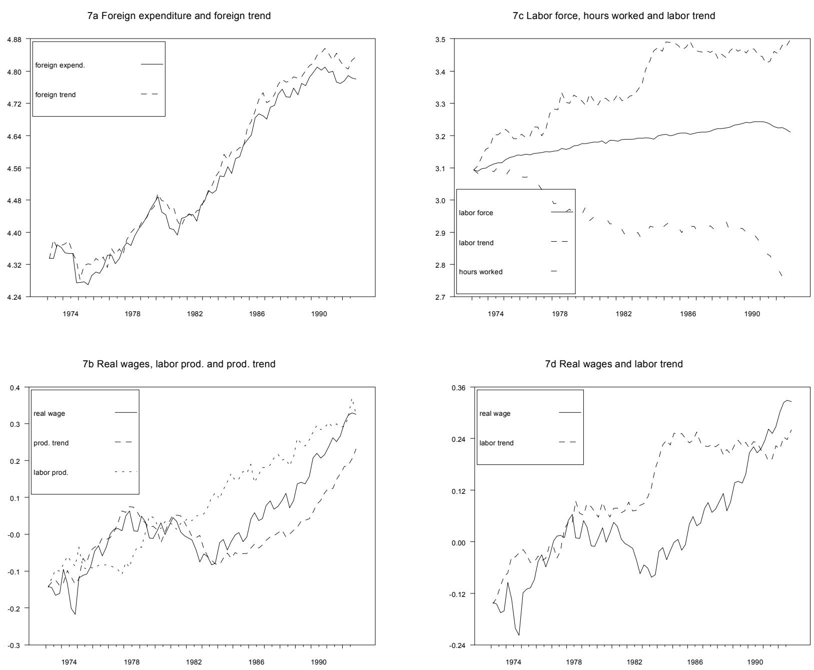

Figure 7: The estimated trends together with other variables

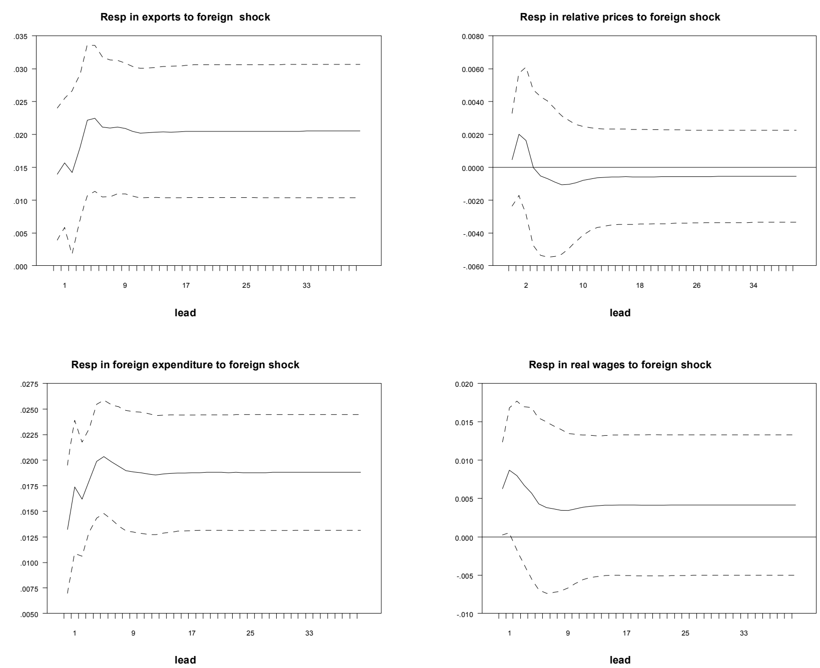

Figure 8: Impulse response functions, with 95 percent confidence bands, from a one standard deviation shock to the foreign trend

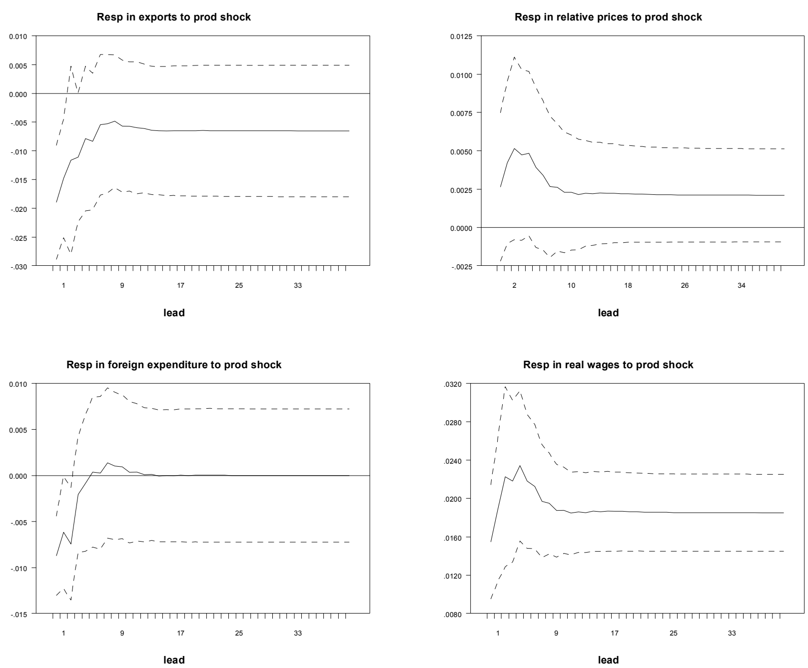

Figure 9: Impulse response functions, with 95 percent confidence bands, from a one standard deviation shock to the productivity trend

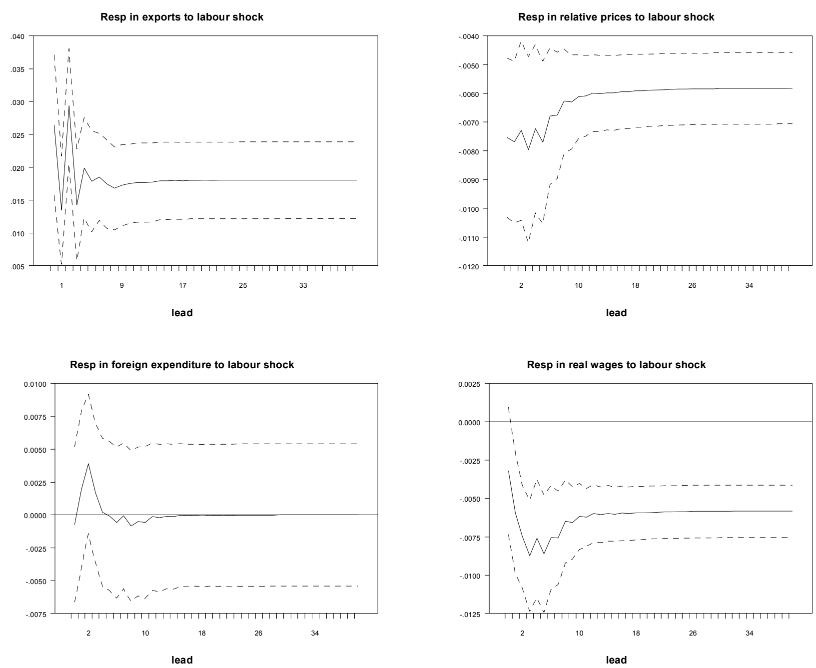

Figure 10: Impulse response functions, with 95 percent confidence bands, from a one standard deviation shock to the labor supply trend

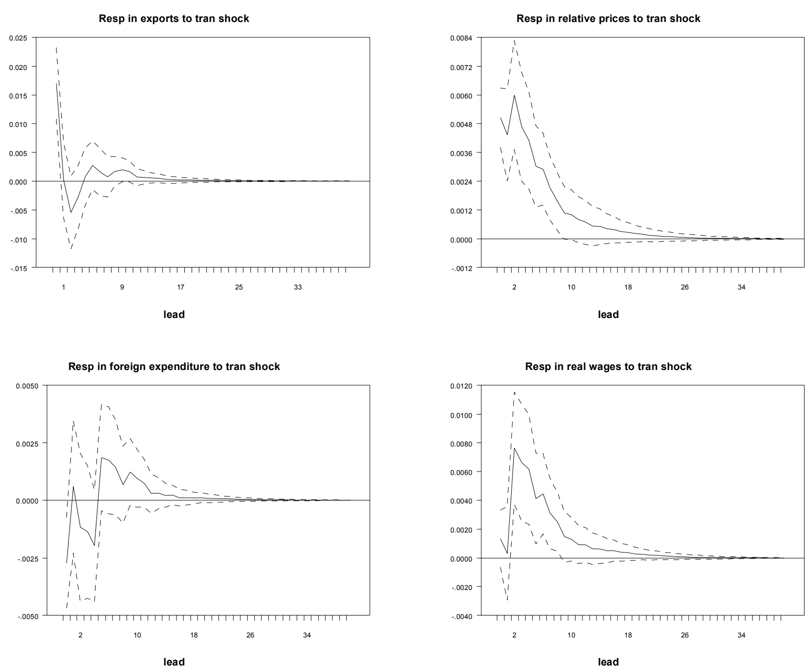

Figure 11: Impulse response functions, with 95 percent confidence bands, from a transitory shock

Essay IV
Random and stock-flow models of labour market matching—Swedish evidence*

1 Introduction

Labour markets are characterised by frictions, implying that the reallocation of jobs and workers normally involves the coexistence of unemployment and vacancies as well as large flows of jobs and workers. An efficient matching process in the labour market contributes to both lower unemployment and higher employment rates. Hence, it is a prominent policy target to promote an efficient matching between vacancies and job seekers in the labour market. This, to be effective, creates a need for good indicators for labour market matching efficiency. Shifts in Beveridge curves have often been used as evidence of changes in matching efficiency. However, Beveridge curves may shift for a number of reasons, not all connected to the efficiency of the matching process.[1] A more direct way to look at matching is by means of aggregate matching functions. Estimated matching functions, typically giving the number of matches as a function of the numbers of vacancies and job seekers, provide information on how matching efficiency, reflecting labour market frictions, has evolved. Over time, an increasing number of empirical studies using a matching function framework has accumulated.

*Coauthored by Anders Forslund. We are grateful for comments on earlier versions from Barbra Petrongolo, Kåre Johansen and Bertil Homlund as well as seminar participants at IFAU and the Department of Economics, Uppsala University. The usual caveat applies.

[1]It is, for example, well known that changes in the inflow rate to unemployment, *ceteris paribus*, give rise to shifts in the Beveridge curve.

Empirical results, presented in a recent survey of the matching function literature (Petrongolo and Pissarides, 2001), indicate that matching functions have been unstable in a way consistent with deteriorating matching efficiency in several OECD countries. However, the analysis in Gregg and Petrongolo (2004) suggests that the instability in estimated matching functions partly reflects mis-specification problems. More specifically, the authors point to problems of time aggregation when using discrete-time data (Burdett, Coles, and van Ours, 1994; Berman, 1997) and the existence of non-random matching, leading to so called stock-flow matching models (Coles, 1994; Coles and Smith, 1998; Coles and Petrongolo, 2003; Gregg and Petrongolo, 2004).

There are only two previous studies (Edin and Holmlund, 1991; Hallgren, 1996) of matching functions on Swedish data. Neither of them explicitly considers the stability of the matching function. Instead, their main focus is on the contribution of active labour market programmes to matching.

In the present paper we estimate aggregate matching functions, paying special attention to time aggregation and stock-flow matching. In doing this, we take advantage of a rich data base, that enables us to compute observations on the variables entering the matching function at (virtually) any frequency we choose. This means that we can assess the importance of the time aggregation problem. We can also generate stocks, outflows and inflows of vacancies and job seekers at any chosen frequency. Hence, we can also shed light on the importance of stock-flow matching.

We have also experimented (quite a lot) with different regional matching models, e.g. allowing (parametrically) for spatial correlations. However, all results of those experiments led to the conclusion that nothing was gained by disaggregating across regions. We also tried to disentangle differential effects in the matching process of openly unemployed and participants i active labour market programmes as well as of unemployed with different unemployment spell durations. Neither of these exercises gave any reasonable results and are, hence, not reported.

2 The matching function

The *matching function* is a way to summarise the results of the efforts of workers looking for jobs and firms looking for workers to fill vacancies. This is a complicated process involving a large variety of activities. The usefulness of the matching function as an analytical device hinges critically on the assumption that the complicated matching process can be summarised by a (reasonably) stable function that relates the number of matches at any point in time to the number of job-seekers, the number of vacancies and (possibly) a small number of other variables.

The simplest matching function can be written

$$M_t = m(U_t, V_t);\ m_1 > 0,\ m_2 > 0 \tag{1}$$

where M_t is the number of matches (jobs formed) in a given point in time, U_t is the number of unemployed job seekers[2] and V_t is the number of vacant jobs.[3]

Random matching Under random matching unemployed workers and vacancies are randomly selected from U_t and V_t and job seekers find jobs and vacancies are filled at the Poisson rates $\lambda_{U_t} = M_t/U_t$ and $\lambda_{V_t} = M_t/V_t$, respectively.

The number of matches over any time period (the length of which we normalise to 1) is then given by

$$M = \int_0^1 m(U_t, V_t)\mathrm{d}t = \int_0^1 U_t \lambda_{U_t} \mathrm{d}t \tag{2}$$

U_t is, in turn, given by

$$U_t = U_0 \exp\left(-\int_0^t \lambda_{U_s} \mathrm{d}s\right) + \int_0^t u_{t'} \exp\left(-\int_{t'}^t \lambda_{U_s} \mathrm{d}s\right) \mathrm{d}t' \tag{3}$$

where U_0 is the beginning of period unemployment stock and u_t is the inflow into employment during the period.

To estimate (2), one must assume something about the within-period development of the inflow of new unemployed, u_t and the outflow rate λ_{U_t}. The assumptions here will be $u_t = u$ and $\lambda_{U_t} = \lambda_U$. Substituting these into (3) and then into (2), we get unemployment outflow (matches) as

$$M_U = \left(1 - e^{-\lambda_U}\right) U_0 + \left(1 - \frac{1 - e^{-\lambda_U}}{\lambda_U}\right) u \tag{4}$$

The message of *Equation* (4) is that the number of matches depends on the outflow rate λ, the beginning-of-period stock of job seekers and the within-period inflow of job seekers. The outflow rate will under random matching be the same of "old" and "new" job seekers.

[2]More generally, we could include all job seekers, for example participants in labour market programmes and "on-the-job" seekers, not only the unemployed.

[3]A number of additional assumptions are often imposed and sometimes tested (for example concavity, homogeneity of degree 1, $m(0, V) = m(U, 0) = 0$).

The time aggregation problem when estimating (4) on discrete-time data arises because the second term on the right-hand side involves the inflow of job seekers, which is typically not observed. If the inflow of new job seekers is non-trivial compared to the stock, the measurement error will also be non-trivial and result in potentially seriously biased estimates.

Stock-flow matching Under stock-flow matching, the story is that workers flowing into unemployment first sample the stock of vacancies and some immediately match. The remaining, unmatched workers (the stock) will sample the inflow of vacancies and leave unemployment at some rate. We represent this by letting the probability of direct matching be p_u. With probability $1 - p_u$ unemployed workers must wait for new vacancies to match at the rate λ_U. Under the same assumptions as under random matching, we get the following unemployment outflow equation under stock-flow matching:

$$M_U = \left(1 - e^{-\lambda_U}\right) U_0 + \left[1 - \frac{1 - p_u}{\lambda_U}(1 - e^{-\lambda_U})\right] u \tag{5}$$

The main difference between the expression (5) under stock-flow matching and its counterpart (4) under random matching is that a proportion p_u of the within-period inflow of job seekers will match immediately.

3 The data

3.1 Data sources and definitions

The data used in the empirical analysis derive from the *HÄNDEL* data base collected by the National Labour Market Board (LMB) since August, 1991. This data base includes records of all contacts between job seekers and the employment offices of the Public Employment Service (PES). These contacts result in a categorisation of job seekers into openly unemployed and participants in different labour market programmes. When a job seeker leaves the register, a destination is specified. From this register we have constructed series of stocks of openly unemployed and programme participants as well as inflows, all at the municipality level. As the records are daily, we could in principle compute daily figures for our variables. We have, however, chosen to compute data weekly, monthly and quarterly.[4] These series form the basis of our measures of job seekers. The outflow of job seekers to work, taken from the same source, is one of the two measures of the number of matches we

[4]We believe that daily series would be plagued by too much measurement error.

use. Although there are problems in the registers (Bennmarker, Davidsson, Forslund, Hemström, Johansson, Larsson, Martinsson, and Persson, 2000), we believe that we measure our variables of interest with reasonable accuracy in most cases. The possible exception is the measure of outflow to jobs. A substantial fraction of the job seekers leave the register for unknown reasons. Studies by Bring and Carling (2000), Sahin (2003), and Forslund, Johansson, and Lindqvist (2003) indicate that roughly 50 % of these actually leave the register for a job. Hence, as a baseline we add 50 % of those leaving the register for unknown reasons when we compute the number of matches. We have checked the importance of this and the results with and without this addition were very similar.

The registers from the LMB also include information of vacancies. We have used these raw data to compute vacancy stocks and inflows as well as outflows of vacancies[5] as an alternative measure of the number of matches. Reporting of vacancies to the public employment service (PES) is mandatory in Sweden. However, it is well known that far from all vacancies are reported to the PES.[6] It may also very well be the case that coverage varies over time. Statistics Sweden has recently started collecting vacancy data by survey methods, but these time series are as yet too short to be useful in our analysis. Hence, there is reason to believe that we have measurement errors in our vacancy data.

The exact data definitions are presented in *Appendix A*.

3.2 A brief description of the aggregate data

The data (seasonally adjusted) are plotted in *Figures 1* and *2*. A number of points are worth noting. *First*, the correlation between the outflow and inflow of job seekers is higher than the correlation between the outflow and the stock of job seekers, although the difference is not staggering (0.54 as compared to 0.47). Looking instead at vacancies, the correlation between the inflow and the outflow is 0.16, whereas the stock and the outflow are negatively correlated.[7]

To some extent these patterns in the data indicate that increases in matching to a non-trivial extent are driven by increased inflows of vacancies and unemployed with stocks much less volatile. Similar patterns are also found

[5]The part of the outflow that represents filled vacancies rather than "withdrawn" vacancies.

[6]See, for example, Ekström (2001), where the results of a survey to firms concerning their modes of recruiting personnel are reported.

[7]The correlation is -0.17.

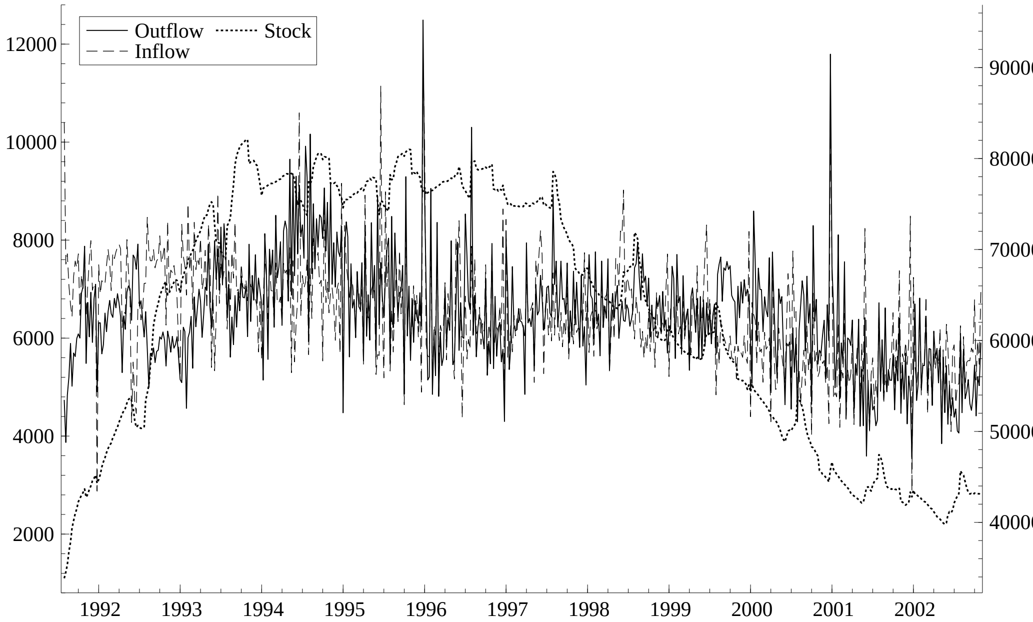

Figure 1: Weekly inflow, outflow (left-hand side axis), and stock of job seekers (right-hand side axis).

in the UK (Gregg and Petrongolo, 2004) and the US (Blanchard and Diamond, 1989).

Looking at the time series properties of the variables, ADF tests forcefully reject non-stationarity in all flows, whereas the results for the stocks are somewhat ambiguous.[8]

Further inspection of *Figure 2* reveals that even the weekly inflow of vacancies is of a non-trivial size compared to the stock. This should serve as yet a warning against the use of the beginning of period stock as a measure of available vacant jobs over a week, and of course even more so if the time period under consideration is longer. This time-aggregation problem is less serious for the unemployed job seekers, where the inflow is much smaller relative to the stock. This difference between vacancies and unemployment is a mirror image of the durations of the spells, which are plotted in *figures 3* and *4*.

Figure 3 shows the development of the duration of ongoing and completed

[8]The test results depend on the presence of a deterministic trend.

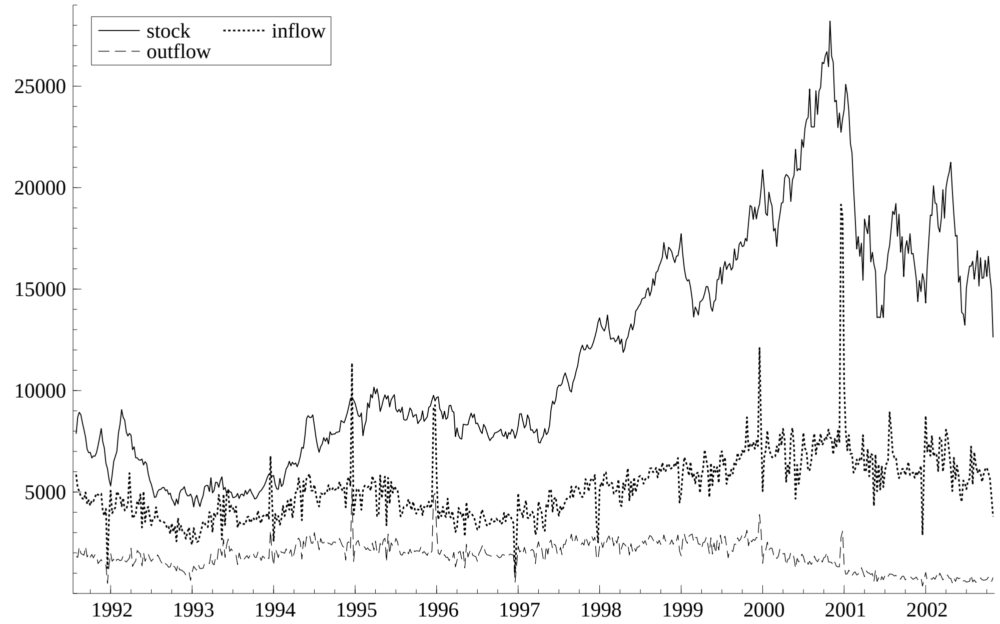

Figure 2: Inflow, outflow, and stock of vacancies (weekly)

spells of unemployment from late 1991 to late 2002.[9] The development in the early 1990s is partly an artifact reflecting that the register begins in August, 1991. Some spells starting earlier have a recorded starting date, but some do not. This means that the rise in duration is overestimated. However, we see that the average spell typically lasts between some 30–40 weeks (completed spells) and 60–80 weeks (ongoing spells).

Figure 4 shows the development of the duration of vacancy spells (filled and unfilled). These durations are much shorter than the unemployment durations shown in *Figure 3* (between 1 and 2 weeks for filled vacancies). However, also for vacancies it is true that the average duration of spells in the vacancy stock is significantly longer than the average duration of the filled vacancies.

The observation that the durations for ongoing spells of unemployment and vacancies are significantly longer than for the completed spells is clearly at odds with the predictions of random matching models, where we would

[9]What we actually measure is the duration of spells in the registers of the National Labour Market Board, where cycling between open unemployment and participation in ALMPs is counted as a continuous spell.

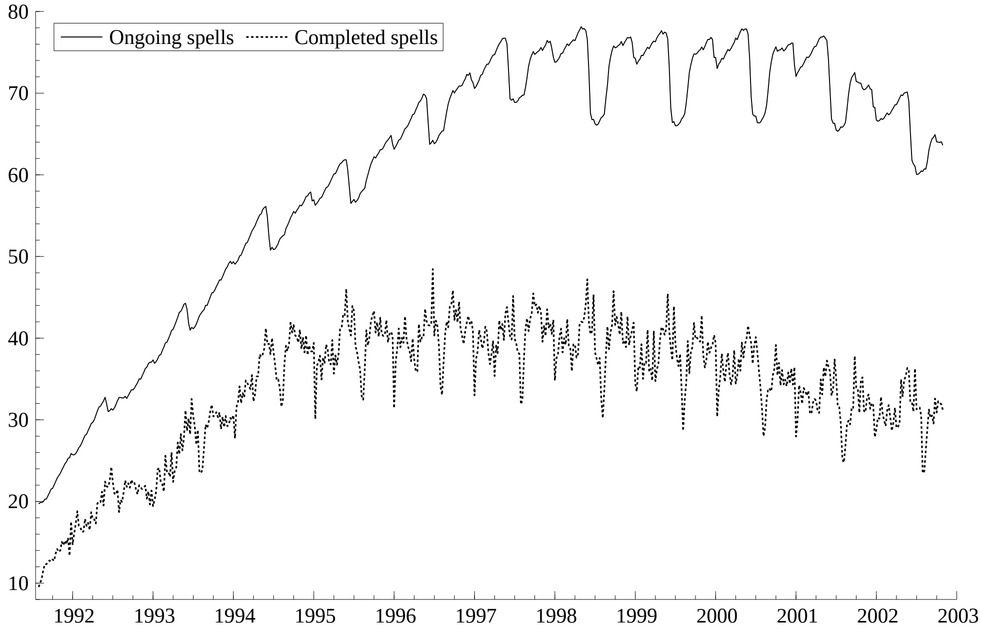

Figure 3: Average duration (weeks) of ongoing and completed unemployment spells

expect ongoing and completed spells to be of equal length in a steady state. The observed pattern is, however, possibly consistent with predictions of the stock-flow matching framework presented in *Section 2*.

3.3 The job seekers

Our data base contains information that enables us to describe the job seekers in some detail. In *Table 1* we show the numbers of persons in different categories of job seekers as well as the outflow rates to jobs[10] from each of these categories. We show the job seekers by the duration of the spells in the registers of the PES as well as by "type" of job seeker (i.e., openly unemployed, programme participants, employed job seekers and those part-time unemployed, employed by the hour or temporary employed; all according to the PES registers).

Looking first at the number of persons in different categories of job seekers, we see that openly unemployed and programme participants force-

[10]The weekly outflow in relation to the stock.

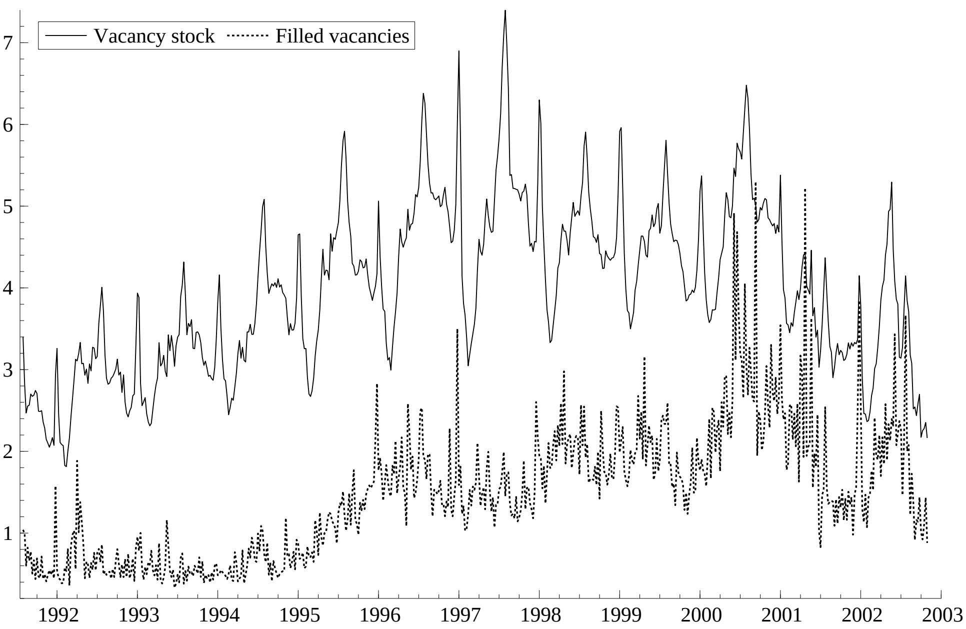

Figure 4: Average completed and uncompleted vacancy duration (weeks)

fully outnumber the different types of employed (or semi-employed) job seekers in our data base. In terms of outflow rates to jobs, the unemployed and the category including temporary employed and other "semi employed" persons exit to jobs much more rapidly than employed job seekers and, especially, programme participants. This feature would suggest that one could gain by disaggregating across different types of job applicants in the estimation of the matching functions.[11]

Looking next at job seekers with different spell lengths, the exit rates to employment decrease by spell lengths almost monotonically, the main exceptions being exit rates from spells lasting between 60 and 90 days. As programme participants, almost by construction, have longer spells than the openly unemployed on average, there is a problem in the separate identification of the contributions of openly unemployed job seekers and programme participants on the one hand, and job seekers with different durations of spells on the other hand. Earlier findings (Edin and Holmlund, 1991; Hallgren, 1996) that programme participants contribute to matching to a lesser ex-

[11] As we mentioned in *Section 1*, we tried such model specifications, but without getting any reasonable results.

Table 1: Some characteristics of different categories of job seekers

Category	Average number of persons	Average weekly outflow rate
By type of job seeker:		
Openly unemployed	317 106	.021
Programme participants	146 712	.004
Employed job seekers	29 477	.009
Temporary employed, employed by the hour, part-time employed	59 500	.020
By duration of spell:		
0–30 days	43 043	.032
31–60 days	39 436	.020
61–90 days	36 341	.032
91–120 days	26 509	.026
121–240 days	84 229	.021
241–360 days	54 852	.016
361–480 days	38 735	.012
481–600 days	28 645	.010
>600 days	112 027	.007

tent than the openly unemployed hence may reflect duration dependence or selection as well as programme effects per se.

4 Econometric specification

Let M_t denote the expected flow matching rate at time t. Then

$$M_t = p_t u_t + \lambda_t U_t \tag{6}$$

where u_t denotes the inflow of job seekers, p_t the proportion of these that match immediately, U_t the stock of job seekers and λ_t the rate at which the stock matches.[12] We have experimented with estimating models for both the outflow to work of job seekers and the outflow of vacancies. The latter models did not, however, give any sensible results, so we restrict our discussion to the outflow of job seekers.

In discrete time, equation (6) can be written

$$M_t = a_t U_{t-1} + b_t u_t + \varepsilon_t \tag{7}$$

[12] The exposition follows the presentation in Gregg and Petrongolo (2004), where more details are found.

We now use the expressions derived in *Section 2* to specify a_t and b_t for both random matching and stock-flow matching.

Random matching Under random matching we have (see Equation (4))

$$\begin{aligned} a_t = &\quad 1 - e^{-\lambda_U} \\ b_t = &\quad 1 - \tfrac{1-e^{-\lambda_U}}{\lambda_U} \end{aligned}$$

To complete the specification of the random matching model, a functional form for the matching equation (1) must be chosen. If it is assumed to be a constant-returns Cobb-Douglas function, we get

$$\lambda_{U_t} = \exp\left[\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right)\right] \tag{8}$$

Stock-flow matching Under stock-flow matching we get

$$\begin{aligned} a_t = &\quad 1 - e^{-\lambda_U} \\ b_t = &\quad \left[1 - \tfrac{1-p_u}{\lambda_U}(1 - e^{-\lambda_U})\right] \end{aligned}$$

and

$$\lambda_{U_t} = \exp\left[\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right) + \alpha_2 \ln\left(\frac{v_t}{U_{t-1}}\right)\right] \tag{9}$$

Next, we also allow the instantaneous matching probability (p_u) of the unemployment inflow to dependent on labour market conditions:

$$p_{u_t} = \exp\left[\gamma_0 + \gamma_1 \ln\left(\frac{V_{t-1}}{u_t}\right)\right] \tag{10}$$

Finally, we include a quadratic trend in the expressions for λ_{U_t} and p_{u_t}, either imposing the same trend for both or estimating separate trends for λ_{U_t} and p_{u_t}[13]

Comparing the models for random matching and stock-flow matching, we see that the latter models reduce to the former if $\alpha_2 = 0$ and $p_u = 0$, whereas stock-flow matching implies $\alpha_1 = 0$. These restrictions are easily tested.

[13]Estimates of models with separate trends did not converge unless other restrictions were imposed and are not reported.

5 Results

Our data enable us to look closer into some issues discussed in the introduction. First, to discuss problems of time aggregation, we will show estimates of aggregate log-linear matching functions using weekly, monthly and quarterly data. In doing this, we both use beginning-of-period stocks of vacancies and job seekers and input measures that include half of the inflows during the period in question. Burdett, Coles, and van Ours (1994) showed that if stocks are mean reverting, then the use of beginning-of-period stocks gives rise to a downward bias in matching elasticities with respect to vacancies and job seekers and that this bias is an increasing function of the length of the time interval. The use of the beginning-of-period stocks plus half the inflow is a solution to this problem that has been suggested by Gregg and Petrongolo (1997) and follows from a Taylor expansion of $\exp(-\lambda)$ around $\lambda = 0$ in *equation* (4).

The main part of our results, however, pertain to whether random matching or stock-flow matching seems to be a better description of the matching process in the Swedish labour market.

Employed job seekers In Petrongolo and Pissarides (2001) it is shown that, under reasonable assumptions, neglecting employed job seekers when measuring the total number of job seekers will produce biased estimates of the parameters in the matching function.[14] In our data, we have information on employed job seekers who are registered at the PES. The estimated models all use measures of the number of job seekers including the number of employed job seekers as well as the number of part-time unemployed, temporarily employed and those employed by the hour. Our measures of the outflow to employment, consequently, includes not only the unemployed and the programme participants, but also employed job seekers and part-time unemployed, temporarily employed and those employed by the hour changing employment status to “more” employment.

The number of job seekers To sum up our discussion of measurement issues, we end up using a measure (used in all estimated models) of the number of matches containing the following components:

1. Openly unemployed job seekers leaving the register for work

[14] Job search among the employed is most likely rather responsive to labour market tightness. If this is the case, the effect of vacancies on the number of matches will be under-estimated and the effect of unemployed job seekers over-estimated.

2. Programme participants leaving the register for work
3. Employed job seekers and part-time unemployed, temporarily employed and those employed by the hour changing employment status to "more" employment
4. Half the number of persons leaving the register for unknown reasons

Although not flawless, this measure should be considered accurate in comparison with most alternatives previously used to estimate Swedish matching functions.[15]

5.1 Random matching: log-linear matching functions

To check how sensitive the estimates are to the sampling frequency in the data, we have estimated standard log-linear matching functions on weekly, monthly and quarterly data. We have also used lagged stocks plus half of the inflow of vacancies and unemployment (at the same frequencies) as regressors. The results are displayed in *Table 2*.[16]

By and large, the results are consistent with the theoretical predictions. Hence, the estimated scale elasticity is decreasing with decreasing measurement frequency in the data. Furthermore, for each frequency, the estimated scale elasticity is higher when the measures of job seekers and vacancies include half the inflow during the period than when the beginning-of-period stocks are used. In fact, all point estimates of the scale elasticity is well below unity and only non-significantly different from unity in the model estimated on weekly data including the half of the inflows during the week of vacancies and job seekers.

The estimated elasticities are generally much higher for job seekers than for vacancies. This may, of course, reflect measurement error in the vacancy series. However, the finding seems to be fairly consistent with the results reported in Petrongolo and Pissarides (2001), although results vary a lot.[17]

[15] Previous Swedish studies have mainly used knowledge of the inflow of vacancies and vacancy stocks to construct a measure of the outflow of vacancies.

[16] The same models have been estimated using an outflow measure excluding those leaving the register for unknown reasons. The results were qualitatively similar, but the fit was worse.

[17] Estimating models including quadratic time trends generally give somewhat higher point estimates for vacancies and somewhat lower point estimates for the number of job seekers. The estimated scale elasticities are fairly similar in those models, except for the models estimated on quarterly data, where the estimated scale elasticities increase quite a lot, especially in the model including half of the within-period inflows, where the estimated elasticity is significantly greater than unity (point estimate 1.64).

Table 2: Estimated log-linear matching functions: Sweden, weekly, monthly, and quarterly data 1991-2002. The outflow includes half of those leaving the register for unknown reasons.

	1	2	3	4	5	6
Frequency	weekly	weekly	monthly	monthly	quarterly	quarterly
Variable						
const	2.03	-1.73	4.82	3.66	7.68	5.61
	(1.24)	(1.59)	(1.48)	(1.45)	(1.18)	(1.76)
V_{t-1}	0.06	—	0.15	—	0.08	—
	(0.03)	—	0.04	—	(0.03)	—
U_{t-1}	0.47	—	0.32	—	0.24	—
	(0.08)	—	(0.09)	—	(0.07)	—
$V_{t-1} + .5 \times v_t$	—	0.24	—	0.22	—	0.15
	—	(0.05)	—	(0.05)	—	(0.06)
$U_{t-1} + .5 \times u_t$	—	0.63	—	0.35	—	0.32
	—	(0.10)	—	(0.12)	—	(0.09)
Scale elast. μ	0.53	0.87	0.47	0.57	0.32	0.47
$P(\mu = 1)$	0.0000	0.30	0.0000	0.0003	0.0000	0.0006
$\bar{R}^2$	0.47	0.49	0.46	0.45	0.69	0.69

Newey-West standard errors in brackets. Data seasonally adjusted. Error term assumed to follow AR(5) process and parameters for this process have been estimated (but not reported in the table) using Eviews.

5.2 Testing for stock-flow matching

To test whether matching is better described as random matching or stock-flow matching we have estimated the models presented in *Section 4*. The results are presented in *Table 3*.[18]

In the first column of *Table 3*, the estimates of the specification corresponding to random matching are given. The estimates suggest a significant effect of the lagged stocks of job seekers and vacancies and a transition rate to jobs at about 1 % a week, implying an average duration of unemployment spells equal to just above 80 weeks evaluated at sample means of the variables.

In column 2, the estimates of the simplest form of stock-flow model are displayed. The point estimate of the lagged stocks now drops and is not significantly different from zero. At the same time, the point estimate capturing the effect on the outflow to jobs of the inflow of vacancies is highly significant

[18]A number of other specifications were tested. Measuring the outflow to employment without those leaving for unknown destinations produced very similar results, as did estimating models with more restrictive definitions of job seekers and corresponding outflows. When estimating models with separate trends for λ and p, convergence was not achieved unless other restrictions were imposed.

Table 3: Estimated unemployment outflow equations: Sweden 1991–2002, weekly data. The dependent variable includes half of the outflow to unknown destinations.

	1	2	3	4	5	6
	Model 1	Model 2	Model 3	Model 3	Model 2 trend	Model 3 trend
λ_U	[0.01]	[0.007]	[0.005]	[0.006]	[0.01]	[0.004]
α_0	-3.66	-3.22	-3.89	-3.36	-2.85	-3.79
	(0.12)	(0.15)	(0.50)	0.18	(0.32)	(0.53)
α_1	0.19	*0.02*	*-0.19*	0	*0.09*	*-0.26*
	(0.03)	(0.04)	(0.15)	—	(0.07)	(0.19)
α_2	—	0.36	0.44	0.36	0.40	0.57
		(0.04)	(0.07)	0.03	(0.04)	
p_u	—	0.21	[0.27]	[0.23]	0.22	[0.30]
	—	(0.01)			(0.01)	
γ_0	—	—	-1.28	-1.47	—	-1.15
			(0.14)	0.08		(0.15)
γ_1	—	—	0.17	0.06	—	0.24
			(0.08)	0.04	(0.07)	
t	—	—	—	—	0.13	0.07
					(0.05)	(0.02)
t^2	—	—	—	—	-0.0003	-0.0002
					(9.3×10^{-5})	
R^2	0.43	0.66	0.66	0.66	0.66	0.67

Seasonally adjusted data. Dependent variable: weekly unemployment outflow. Estimated with nonlinear least squares; the error term was assumed to follow an AR(5) process and the parameters of the process were estimated, but not reproduced in the table. Asymptotic standard errors in brackets. Parameters that are not significant at the 5 % level in italics. Numbers in square brackets are computed from the estimated parameters using the specification of the model in question.

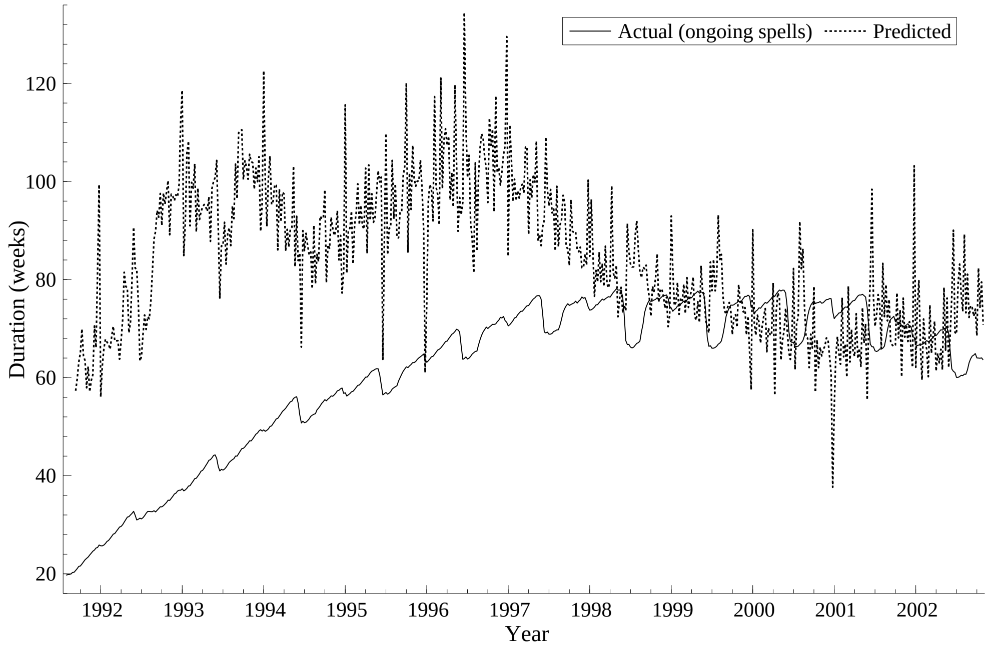

Figure 5: Actual and predicted duration of register spells of job seekers

as is the estimate of the proportion of job seekers immediately finding a job. This pattern is clearly consistent with stock-flow matching and inconsistent with random matching. Turning to the estimates of the other, more general, formulations, the same conclusion follows. Hence, the estimates forcefully reject random matching in favour of stock-flow matching.

The estimated models can be used to predict the duration of unemployment spells. To do this, we generate an estimate of the outflow rate by relating the number of predict matches to the (lagged) stock of job seekers, $\widehat{\lambda_t} = \widehat{M_t}//U_{t-1}$. The inverse of $\widehat{\lambda_t}$ then gives the predicted duration. All estimated models give rise to fairly similar patterns of predicted durations. In *Figure 5* we show durations of ongoing spells and the predictions derived from the model in the sixth column of *Table 3*.

Comparing the actual and the predicted durations, we see that the predictions are systematically higher than the actual values roughly until 1998. Partly, this reflects an artifact of the data—the register starts in August, 1991, and for most early spells in the register beginning before this date, there is no information about when spells actually started. Another difference is that the predicted durations are both forward-looking and myopic in the sense that they show how durations would evolve given a constant outflow rate from each point in time. The actual values, on the other hand, are the results of historical outflow rates. Hence, unless in a steady state we should not expect the two to coincide.[19]

6 Concluding comments

In this paper we have estimated a number of matching models using a data base with information on stocks, inflows and outflows of job seekers and vacancies from which we can compute data at virtually any frequency. Our main purposes have been to test whether matching is best described by random matching or stock-flow models of matching and to shed light on the importance of the data frequency for the parameter estimates in standard log-linear matching models.

Regarding the choice between random matching and stock-flow matching, our evidence forcefully rejects random matching—the parameter estimates in all estimated model specifications are consistent with stock-flow matching and inconsistent with random matching. More precisely, we find that a non-trivial of new job seekers match instantly (within the first week). We also find that stocks of "old" vacancies and job seekers do not contribute significantly to matching, whereas the inflow of vacancies matches with the lagged stock of job seekers.

Consistent with theoretical predictions, we find that the use of lagged stocks as right-hand side variables in matching functions (i.e., failing to take account of the within-period inflow of job seekers and vacancies) gives lower estimates of matching elasticities and that this is more pronounced the lower the measurement frequency. This evidence provides a warning against strong beliefs in estimates of the scale elasticity of the matching function derived from annual or quarterly data.

The main caveat when interpreting our results is that there are good reasons to believe that there are measurement errors in our vacancy data, which most likely may have biased our matching elasticities with respect to vacancies downwards. Measurement error may also be the reason behind our failure to estimate any sensible model of the outflow of vacancies.

[19] Apart from possible complications arising from heterogeneity.

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Appendix

A Data definitions

All data used derives from the data base "Händel" of the National Labour Market Board. This data base is available from August, 1991 and onwards. Our sample runs from August, 1991, through October, 2002.

The number of matches The number of matches equals the outflow to jobs irrespective of the previous state in the data base. This means that we, in addition to openly unemployed job seekers and labour market programme participants, have included the outflows of employed job seekers, part-time unemployed, temporarily employed and those employed by the hour who change status. We have experimented with more narrow definitions, but results were similar. The basic frequency used is the outflow over a week.

The number of job seekers The number of job seekers is the total number of individuals in the data base except fishers, job seekers applying for jobs outside Sweden, disabled and those on sabbatical leave (who are not allowed to take a job). This stock is measured at the end of each week.

The inflow of job seekers The inflow of job seekers includes the total inflow (during a week) to the data base.

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